

DISCUSSION PAPER SERIES

IZA DP No. 12534

Crime and Networks: 10 Policy Lessons

Matthew J. Lindquist
Yves Zenou

AUGUST 2019

DISCUSSION PAPER SERIES

IZA DP No. 12534

Crime and Networks: 10 Policy Lessons

Matthew J. Lindquist

SOFI, Stockholm University

Yves Zenou

Monash University and IZA

AUGUST 2019

Any opinions expressed in this paper are those of the author(s) and not those of IZA. Research published in this series may include views on policy, but IZA takes no institutional policy positions. The IZA research network is committed to the IZA Guiding Principles of Research Integrity.

The IZA Institute of Labor Economics is an independent economic research institute that conducts research in labor economics and offers evidence-based policy advice on labor market issues. Supported by the Deutsche Post Foundation, IZA runs the world's largest network of economists, whose research aims to provide answers to the global labor market challenges of our time. Our key objective is to build bridges between academic research, policymakers and society.

IZA Discussion Papers often represent preliminary work and are circulated to encourage discussion. Citation of such a paper should account for its provisional character. A revised version may be available directly from the author.

ISSN: 2365-9793

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Crime and Networks: 10 Policy Lessons*

Social network analysis can help us understand more about the root causes of delinquent behavior and crime and provide practical guidance for the design of crime prevention policies. To illustrate these points, we first present a selective review of several key studies and findings from the criminology and police studies literature. We then turn to a presentation of recent contributions made by network economists. We highlight 10 policy lessons and provide a discussion of recent developments in the use of big data and computer technology.

JEL Classification: A14, K42, Z13

Keywords: co-offending, crime, criminal networks, social networks, peer effects, key player

Corresponding author:

Yves Zenou
Department of Economics
Monash University
Caulfield East VIC 3145
Australia
E-mail: yves.zenou@monash.edu

* We would like to thank Philip Cook, Sanjeev Goyal, Cameron Hepburn, Magne Mogstad, Alex Teytelboym and one anonymous referee for their comments and suggestions. Our work is funded in part by the Swedish Research Council (Vetenskapsrådet).

1. Introduction

It comes naturally to many of us to think about delinquency and crime in terms of networks. Just think of your favorite TV detective sitting in the operations room of her precinct, pinning up pictures of gang members and organizing them on the board in a hierarchical pyramid, or placing strings between victims and suspects in order to visualize the potential relationships between them. Her goal is to map out the relations between these individuals in order to come up with an effective way of solving the crime in hand and preventing more crime in the future. But are such network mapping exercises truly helpful? Could a broader set of network analysis tools be used to inform crime policy more generally? And if so, then how might network economists contribute to such a development?

In this article, we argue that social network analysis can be used in a meaningful way to help us understand more about the root causes of delinquent behavior and crime and also to provide practical guidance for the design of crime prevention policies. To illustrate this point, we begin by discussing two existing strands of the networks and crime literature. The first approach is presented in Section 3. This approach analyzes historical data from resolved court cases involving organized crime. Network tools have been used to analyze the structure of such networks to gain insights into their origins, strengths and weaknesses. A second line of inquiry, described in Section 4, is a more hands-on approach and is directly involved in the design of police tactics. To illustrate this second approach, we provide a description of two well-known examples of network based policing policies. We also point out some of the difficulties and potential pitfalls associated with these strategies.

In Section 5, we turn to a presentation of more recent work by network economists. The main difference (as we see it) between the “economic” approach to studying networks and crime and the more traditional approach to studying networks and crime used in the criminology and

police studies literature is that the economic approach explicitly models the behavior of individual agents embedded in a network who face a set of constraints and incentives that affect their choices. The more traditional approach focuses primarily on gleaned useful information from the observed structure of the network. In time, the economic approach may prove itself to be a valuable complement to this more traditional approach; one that provides additional insights on the origins of delinquent behavior and crime and highlights new levers for policy makers to pull on. The economic approach allows us, for example, to think about when group based policies (e.g. changing the group norm) may be more effective than individual based policies (e.g. targeting); and when targeting is more appropriate, the economic approach is much more specific about whom policy makers should target (and why) in order to generate the greatest reduction in crime.¹

At the end of Section 5, we discuss several challenges that are unique to the economic approach to networks and crime. Section 6 presents several more general concerns and discusses recent developments in the use of big data and computer technology; developments that are bound to affect how crime networks are analyzed in the near future. We summarize and conclude in Section 7.

2. Some preliminaries

Before proceeding, we would first like to provide evidence in favor of two of the principle tenets underlying any network analysis of delinquency and crime: (i) delinquency and crime are group

¹ Please note that the nature and format of this article does not allow for a full review of the literature on networks and crime. Our choice of cited articles has, instead, been guided by our wish to make certain specific points and by our desire to focus more on recent work by economists. For those wishing to read more, we can highly recommend two recent anthologies; one edited by Morselli (2014) and the other edited by Bichler and Malm (2015). Both are excellent points of departure for an exploration of this exciting literature. Both provide extensive reference lists. For a recent overview of work done on the economic consequences of social networks, see Jackson et al. (2017).

activities, and (ii) social interactions affect delinquent behavior and crime. We then define some basic terminology from social network analysis that will be used later in this article.

2.1. Is crime a group activity?

Juvenile delinquency is primarily a group activity (Sarnecki 1986, 1990, 2001; Haynie 2001; Warr 2002). McGloin and Nguyen (2014) argue that there is enough empirical support for this claim that it should now be considered a criminological “fact”. Adult convictions, on the other hand, are dominated by solo offenses (see, e.g., Lindquist and Zenou 2014). But this does not necessarily mean that adult crime is not a group activity. In fact, individuals who co-offend are also responsible for the majority of solo offenses. In total, the co-offending population accounts for up to three-fourths of all convictions in the Swedish data used by Lindquist and Zenou (2014). Thus by studying co-offenders and co-offender networks, we are, in fact studying those people who are responsible for committing the majority of crimes in society.

Furthermore, many solo offenses are actually part of a “chain-like transactional setting that incorporates the action of a wide range of participants” (Morselli and Roy, 2008, p. 71). A thief may work alone to steal a piece of property. But he then relies on a “fence” (a middleman) to give him cash for what he steals. This middleman, in turn, sells these goods to an end customer. The thief then takes his cash and buys drugs from his local dealer. Those drugs have made their way from farmer to end user via a production and delivery network. All of these individual actors and individual-level crimes are embedded in a much larger production process. Each solo act is embedded in a network of illegal activities, which (given the right data) can be mapped out and studied.²

² See Tintelnot et al. (2018) for a recent example of a model of domestic production networks with international trade.

Lastly, a large share of more serious crime is, in fact, perpetrated by organized groups of criminals such as the Italian Mafia and street gangs in the U.S. (Kennedy et al. 2001, McGloin 2005; Mastrobuoni and Patacchini 2012; Calderoni 2015). The large focus placed by law enforcement on gangs and organized crime is driven mainly by the high cost to society from these types of group activities.

2.2. Do social interactions affect delinquent and criminal behavior?

There is a growing empirical literature suggesting that peer effects are important in criminal activities. The source of crime and delinquency is located in the intimate social networks of individuals (see e.g. Sutherland, 1947; Haynie, 2001; Sarnecki, 2001; Warr, 2002). Indeed, 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.

In the economic literature, there is also strong evidence showing that peer effects are important in criminal activities. Peers in this literature can be defined as friends (Patacchini and Zenou 2012; Liu et al. 2018), family members (Hjalmarsson and Lindquist 2012, 2013, Eriksson et al. 2016), neighbors (Glaeser et al. 1996; Ludwig et al. 2001; Kling et al. 2005; Damm and Dustmann 2014; Bernasco et al. 2017, Dustmann and Landersø), people that serve time together in prison or juvenile jail (Bayer et al. 2009; Drago and Galbiati 2012; Stevenson 2017), homeless in shelters (Corno 2017), co-workers in the military (Hjalmarsson and Lindquist 2019; Murphy 2019), and groups of co-offenders (Lindquist and Zenou 2014; Phillipe 2017; Bhuller et al. 2018). Importantly, the scope for peer influences may vary by crime type, as may the underlying mechanism.

The literature on social interactions and crime has proposed a number of potential mechanisms to explain how peer effects might work in practice. In theory, the crime of two individuals could be considered substitutes. That is, individual A's crime could "crowd out" individual B's crime if there is a fixed number of criminal opportunities and if the market for crime is congested. But the more empirically relevant case is when the crime of two or more individuals are complementary, such that an increase in individual A's crime increases the crime of individual B as well.

Several hypotheses have been put forth that could explain such a positive spillover effect. 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 co-operating can they make a profit. Since there is no official crime school, mentoring and/or role modeling 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. Group ideologies and norms may either encourage or discourage anti-social behavior 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.

Social network analysis adds another important dimension to this discussion. It shows us that the structure (or architecture) of social relationships between peers can amplify or dampen such peer effects. In fact, having a unique position in the social structure of a gang could get you killed (Papachristos 2009).

2.3. Terminology

A social *network* is a set of individuals (e.g. criminals) or groups (e.g. gangs) that are connected by one or more *links* (or *edges*). Individuals in a network are oftentimes referred to as the *nodes* (or *vertices*) of a network. Links between individuals in a network describe if and how these individuals (or groups) are related to each other. For example, if individuals A and B commit a crime together, then we can use this co-offense to define their relationship; we draw a line between A and B representing this link (as illustrated in Figure 1a). If B also commits a crime together with individual C, and if C does not co-offend with A, then we draw a line between B and C. But we do not draw a line between A and C (as illustrated in Figure 1b).

[Insert Figure 1 about here]

Links in networks may represent a wide variety of different types of relationships and some individuals may have more than one type of relationship that link them together. For example, A and B may also be from the same family or members of the same club. They may own a business together or be friends on Facebook. Figure 1c illustrates the case when A and B co-offend and are members of the same family. Networks that allow for links that represent different types of relationships are sometimes referred to as *multiplex networks*.

Thus far, links have been defined by a mutual and symmetric relationship. In the language of social network analysis, such links are called *undirected*. But links can be *directed* as well. It may be that A sells drugs to B who then sells drugs to C. These directed transactions are represented by the arrows in Figure 1d. Alternatively, we may want to sign an undirected link as being positive or negative. Figure 1e illustrates the case in which gangs A and B cooperate, but gangs B and C are in conflict with each other.

We can also ascribe specific characteristics, such as age, gender or gang affiliation, to individual nodes in the network. In this article, measures of an individual's *network centrality* will be quite important. Having a high network centrality indicates that the person in question may be

an important actor in the network and, perhaps, worth focusing more attention on. Three popular measures of network centrality include *degree* centrality, *eigenvector* centrality, and *betweenness* centrality.

The degree of a node is simply a count of the number of direct links that it has to other nodes in the network. In Figure 1b, individual A has a degree of 1, since he is only connected to one other person. Individual B has a degree of 2, and individual C has a degree of 1. Degree is often viewed as a popularity count. The person with the most friends is considered the most popular.

Degree centrality is measured as the share of individuals in the network that a person is directly connected to. In figure 1b, B has a measure of degree centrality equal to 1 (she has 2 actual links out of 2 possible links) and is the most central agent in the network when using degree to measure centrality.

Eigenvector centrality is frequently used as a measure of power, prestige or influence (Katz 1953, Bonacich 1987). An individual has a high eigenvector centrality when he or she has a high degree and is directly connected to many other high degree people. Note that this measure of centrality relies heavily on the characteristics of an agent's immediate neighbors or friends, and not just on own characteristics. An influential politician, for example, is one that is well-connected to many other well-connected politicians.

Betweenness centrality is not directly related to the number of links a person has. Instead, it reflects the unique position that a person may occupy in the architecture of his or her social network. To calculate betweenness, we first identify all of the shortest paths between any two agents in a network that are not directly connected to each other. In Figure 2a, the shortest path between agents A and C is the walk from A to B followed by the walk from B to C. Then we check if agent B lies on the shortest path between A and C, which she (of course) does. The only way for

A and C to communicate with each other is by going through B. Thus, B has a high betweenness centrality with respect to A and C.

[Insert Figure 2 about here]

More generally, the betweenness centrality of any agent i with respect to any other two agents j and k is defined as the ratio of all shortest paths between agents j and k that agent i lies on, $P_i(jk)$, to all of the shortest paths between j and k , $P(jk)$. If this ratio, $P_i(jk)/P(jk)$, is close to 1 then i lies on most of the shortest paths connecting j and k and, hence, has a high betweenness centrality with respect to agents j and k . If we calculate this ratio for all possible jk -pairs and take their average, then this gives us the betweenness centrality measure for agent i with respect to the entire network.

In Figure 2b, agent B is now situated between two groups of people and not just two individuals. B no longer has the highest degree centrality. Agents A1 and C1 both have more direct links than agent B and, hence, higher degree centralities. But B still holds a unique position in the network since group A and Group C can only communicate through her. B still has the highest betweenness centrality.

Agents with high betweenness centrality have been given many different names in the network and crime literature including bridges, brokers, middlemen, facilitators, and cut-points. Their unique position in the network affords them influence and/or brokerage profits. Removing such a “bridge” or “cut-point” fragments the network into smaller pieces and creates a “structural hole” in the network (akin to missed opportunities) (Burt 1992, 2005).³

Networks can be *dense* or *sparse*. A dense network is one with many links. Figure 3a is an example of a dense network, since all possible links between A, B, C, and D do exist. Figure 3b,

³ There are other measures of network centralities. See Jackson (2008) and Zenou (2016) for an overview of these measures.

on the other hand, is a sparse network, since only 1 out of 6 possible links exists. The *density* of a network tells us the relative fraction of possible links that are, in fact, present. It is the average degree of all of n nodes in the network divided by $n - 1$. A *clique* is a group of individuals that are all completely connected to each other. Figure 3a depicts such a clique. In Figure 3b, agents A and B form their own clique, while agents C and D do not belong to a clique.

[Insert Figure 3 about here]

3. Ex post analyses of organized crime networks

Mastrobuoni and Patacchini (2012) use historical court data provided by the U.S. Federal Bureau of Narcotics (a pre-cursor of the U.S. Drug Enforcement Administration) that include criminal profiles of 800 Italian Mafia members active in the United States during the 1950s and 1960s. The data include information on their criminal associates in the U.S. and on their connections within the Cosa Nostra Mafia in Italy. The leaders of the U.S. Mafia are identified in these files. The data are sourced from several decades of investigative work that was used to raise criminal charges against U.S. Mafia members.

Mastrobuoni and Patacchini (2012) not only map out the criminal relationships between Mafia members, but also their business and family relationships as well. As such, it is an example of a multiplex network analysis. Their analysis confirms the fact that the Mafia is an unusually hierarchical organization. Leaders are well connected (i.e. they have high degree centrality). They are middle aged men, oftentimes born in Sicily (or elsewhere in Italy). Several of the most prominent leaders also have a very high betweenness centrality, which makes them of particular

interest, since high betweenness implies that they acted as bridges or brokers between (otherwise) unconnected Mafia Families.⁴

Of course, in this example, the police investigators had already identified the leaders of these Mafia Families and the researchers simply study the characteristics of these leaders ex post. Work by Calderoni (2015) suggests that related techniques can be used to help identify Mafia leaders and *key players* (as defined in Section 5) at an early stage of the investigative process (which oftentimes span over the course of several years). If so, then this information could be used to target investigative resources towards these individuals.

To identify organized crime leaders, Calderoni (2015) uses data on meeting attendance of members and associates of the ‘Ndrangheta Mafia from Calabria, Italy. These data are part of police investigative records constructed between 2006 and July 13, 2010; at which time the police authorities arrested more than 160 individuals. The network that he studies comprises all of those who attend Mafia meetings (of at least four or more people). The network describes who attended meetings with whom.

Calderoni (2015) shows that analysis of this meeting data can correctly identify the leaders of the ‘Ndrangheta Mafia. Importantly, he shows how the meeting data collected early on in the investigation can be used to predict who the leaders later turn out to be. This implies that law enforcement authorities could potentially use this technique at an early stage of their investigation in order to better identify who they should focus more resources on. Interestingly, betweenness centrality is a key measure for predicting Mafia leaders. Leaders attend meetings that bridge the

⁴ Mastrobuoni and Patacchini (2012) also observe a high degree of intermarriage within Mafia Families. These marriages appear to have strengthened the bonds between already connected Families. They were not used to forge new alliances. In related work, Mastrobuoni (2015) shows how network centrality inside the Italian-American mafia influenced members’ economic prosperity.

communication gap between different Mafia groups; groups that otherwise don't meet and talk on a regular basis.⁵

In hierarchical structures like the Mafia, removing a single leader may have little impact on overall crime, since there is always a lower-level leader in place who is ready to move up in the hierarchy. The Chicago Mafia, for example, continued their operations after their most notorious leader, Al Capone, was put in prison in 1932. To dismantle strong hierarchical structures one may have to adopt a key group strategy as opposed to a key player strategy (Borgatti 2006). This idea is consistent with what we see in the real world. Anti-Mafia investigations tend to take a long time to complete and they are typically concluded by the arrest of a large group of Mafia members.

It is important to keep in mind, however, that most organized crime structures are not as hierarchical as the Mafia. In fact, many can be described as loose associations of independent contractors or brokers, each with their own specific skills or resources. These brokers work in a chain-like crime production system that produces a well-defined product. Arresting one key link can break this chain and lower crime.

Morselli and Roy (2008) study two Canadian car theft operations that exported stolen vehicles to destinations in Europe and Africa. They use police investigative data to describe the chain of transactions carried out in these organized crime networks. Cars are stolen, then hidden, then disguised, then transported, and then sold. Different actors (or brokers) perform very specific tasks at each step. Brokers are only loosely affiliated with each other and several of them performed similar tasks in their legal day jobs. Morselli and Roy (2008) stress that the removal of certain key brokers will disrupt these organizations the most. To define key brokers they use Gould and Fernandez's (1989) concept of brokerage leverage, which builds on the idea of betweenness

⁵ For a more general discussion of the role of betweenness centrality in identify key players in criminal networks see Bright (2015).

centrality but refines it by awarding more importance, or leverage, to those who broker between groups as opposed to those who merely broker between individuals.

Zhang and Chin (2002) and Zhang (2014) study human smuggling from China to the United States. They characterize these organizations as loose affiliations (“ad-hoc task forces”) of connected individuals who possess key resources or knowledge. These organizations have a clear division of labor and limited hierarchical structures. Brokers cooperate in a distinct temporal order to provide a specific product, namely illegal travel services. Zhang (2014) concludes that “From a law enforcement perspective, the implication of understanding the brokerage functions in human smuggling is clear. It is perhaps more effective to target those brokers than any other prolonged investigations aimed at capturing a few major smuggling kingpins. Knowing the weakness of their structural arrangement, law enforcement efforts can therefore have an immediate and pronounce impact.” (p. 129)

Lesson #1 *Identifying key individuals in organized crime networks at an early stage of an investigation allows law enforcement authorities to shift scarce investigative resources towards these individuals.*

Lesson #2 *Betweenness centrality is an important descriptive statistic for identifying key individuals in organized crime. Arresting key individuals may dismantle non-hierarchical crime structures.*

Lesson #3 *Identifying and arresting key groups (as opposed to key individuals) may be necessary for dismantling strongly hierarchical crime structures.*

4. Ex ante network analyses used to inform police tactics

In their seminal piece entitled “The (Un)Known Universe: Mapping Gangs and Gang Violence in Boston”, Kennedy et al. (1997) demonstrate how tools from social network analysis can be used to help the police design more effective policies for solving specific problems. In Boston, the problem was an alarming rise in youth homicides during the early to mid-1990s. This led to the initiation of the Boston Gun Project in 1995 and to Operation Ceasefire in the Spring of 1996 (see Braga et al. 2001 and Kennedy et al. 2001).

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 aided the design of this policy in (at least) two important ways. First, they were able to confirm the police’s own description of the problem; a large share of youth homicides were, in fact, gang-related. Second, they aided the police in identify a small number of key gangs that police could then focus their attention on.

Kennedy et al. (1997) accomplished this using a group-audit method together with a set of tools from social network analysis.⁶ Through these group audits (meetings and discussions with knowledgeable local actors), Kennedy et al. (1997) were able to place gangs on a map of Boston and to mark out their territories. They also placed violent incidents on this map and marked out disputed territories and points of conflict. Undirected links were drawn on these maps between gangs who were allies and between gangs who were in conflict with each other. These later links allowed them to create a gang conflict network superimposed on a Boston city map.

These conflict network data were then used to identify a small number of key gangs that became the focus of the Operation Ceasefire intervention. To identify these key gangs, Kennedy et

⁶ See Sierra-Arevalo and Papachristos (2015) for a clear description of the group-audit method and of how this method can be used in conjunction with social network analysis to aid the design of police programs.

al. (1997) looked at measures of degree centrality, eigenvector centrality, and cliques. Braga et al. (2001) provide convincing evidence that the Operation Ceasefire intervention did, in fact, lead to a significant reduction in youth homicides in Boston.

A key component of the focused deterrence strategy used in the Boston Ceasefire program 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. The police wanted to harness the potential of the group to regulate itself (i.e. they were hoping that more profit-oriented and less hot headed members could enforce some sense of discipline on their more aggressive peers – perhaps by not allowing them the access to guns). But the idea of collective accountability presupposes a well-organized group with the ability to self-regulate, which is not always the case when dealing with street gangs or networks of co-offenders (Sarnecki 2001, Sarnecki and Pettersson 2001, Pettersson 2003, McGloin 2005, 2007).

This last point is clearly illustrated in McGloin's (2005) network analysis of the street gangs in Newark, New Jersey. Using individual level data on gang members, she observes very little cohesion among gang members and, hence, questions whether group accountability would be a credible strategy in this case. Instead, Newark's Operation Ceasefire implemented a deterrence strategy that was focused towards individuals as opposed to groups. Another potential pitfall of the group-oriented policy of collective accountability is that it may, in fact, create a cohesive gang identity among youths who were only loosely connect and where a gang identity had not previously existed (Klein 1971, 1995).

McGloin (2005) also identifies gang members who act as “cut-points” in the Newark gang network data. Removing these individuals from the network would fragment the network. Alternatively, if law enforcement authorities want their new deterrence message to spread as far as

possible and as rapidly as possible, then these are the people that should be told that there is “a new sheriff in town”.⁷

Focused deterrence programs like Operation ceasefire have been implemented in a number of U.S. cities, but with varying success rates. Focused deterrence has been used to combat youth violence and to break up drug markets. Some programs have made use of explicit network methods, while others have not. Some programs have focused attention on groups, while others have focused upon individual actors. Importantly, it remains an open question as to whether or not the success rates of such policies correlate positively with the use of explicit network tools.

In a recent meta-study, Braga et al. (2018) analyze the results of 23 research articles that evaluate the effect focused deterrence strategies used by police in U.S cities (and 1 in Scotland). Overall, focused deterrence does appear to have a crime reducing effect. However, Braga et al. (2018) stress the fact that to date there has been no randomized treatment and controlled experimental evaluation of the focused deterrence strategy. They also argue the program evaluations that have stronger research designs using comparable control groups tend to find much smaller beneficial effects than those found in the original Boston Operation Ceasefire program.

Lesson #4 *Tools from social network analysis can be used as an aid when designing police operational tactics. They tell us who to focus deterrence strategies on.*

Lesson #5 *Street gangs are typically not as well-organized, stable, and cohesive as policy makers tend think they are. Hence, group-oriented policies may not work as intended.*

⁷ Using individual level data also allows one to identify individuals who are only loosely connected to the gang. Schools, churches, and social services could (perhaps) focus their attention on these peripheral youths. They could try and incentivize these youths to leave the gang before getting too deeply involved.

Lesson #6 *There is a need for randomized field experiments to properly evaluate the effects of focused deterrence strategies. These experiments should be designed so that we also learn about the efficacy of network-based strategies versus non-network-based strategies and group-based strategies versus individual-based strategies.*

5. The economic approach to networks and crime

In a nutshell, the economic approach to crime entails (i) writing down an explicit, utility maximizing model of criminal behavior, and (ii) deriving efficient policy counter measures that minimize crime in that model. Gary Becker (1968) was the first researcher to apply such an economic approach to the study of crime. His interest in crime arose one day when he was pressed for time. He had to weigh the cost and benefits of legally parking in an inconvenient garage versus parking in an illegal, but convenient, spot. After roughly calculating the probability of getting caught and then multiplying this probability by the potential punishment, Becker chose to break the law and to park in the illegal parking spot.

Becker extrapolated on this idea and applied it to the study of crime by assuming that criminals make similar rational decisions when committing a crime. He assumed that individuals weigh the potential benefits from committing a crime against the potential costs, which include the risk of apprehension, the probability of a conviction, and the expected punishment. Importantly, the economic model also includes the opportunity cost of time spent committing crime that could have, otherwise, been spent earning a legitimate wage.⁸ This premise of rational decision making

⁸ The simple economic model with a standard utility function also implies that people who are more risk loving will commit more crime and that people who are more impatient (i.e. value the current benefit by more than they disvalue the future punishment) will also commit more crime.

went against the conventional wisdom of the day, that crime was a result of mental illness or social disadvantage. At the time, Beccaria (1764) and Bentham's (1789, 1811) rational choice theory of crime had clearly fallen out of favor among criminologists.⁹

In its first iteration, the standard economic model of crime did not include any recognition of the important social nature of crime. It did not allow for the fact that an individual's rational, utility maximizing behavior could potentially be influenced by the people around him; by their norms, their knowledge, and the legal and illegal opportunities that they provide. In recent years, however, the basic economic model has been extended to include such peer and network effects.¹⁰

Glaeser et al. (1996) were among the first to develop an economic model of crime that allowed for social interactions. In their model, individuals are located in a network on a circle. Some of them are conformists (i.e. they simply copy what their neighbors do), while others decide for themselves whether or not they will commit a crime. In this simple model, Glaeser et al. (1996) show how social interactions can lead to a social multiplier effect that raises aggregate crime.

The network structure studied in Glaeser et al. (1996) is, of course, a very specific one (a circle of neighbors). Richer models have since been developed that allow us to study any network structure. Below, we present a stylized version of such a model that is based on a synthesis of previous models by Calvó-Armengol and Zenou (2004), Ballester et al. (2006, 2010), Patacchini and Zenou (2012), and Liu et al. (2014).

⁹ In this article, rational behavior refers to a decision-making process that obeys a set of standard axioms and is based on making choices that result in the optimal level of utility for an individual. Individuals make criminal decisions that maximize their utility based on a cost-benefit analysis, which includes the influence of their peers either through social learning or through social norms (including peer pressure). The utility maximization problem need not be limited to premeditated criminal acts aimed at maximizing monetary profits and can be amended to include various behavioral biases, such as those studied in Heller et al. (2017). These biases can lead some individuals to make impulsive, short-sighted decisions that are clearly detrimental to their well-being in the long run.

¹⁰ Cook (1980) provides a discussion of an economic model of crime with rational agents making decisions under uncertainty. He argues that "At any time, a robber's perception of arrest and punishment is influenced by his own recent experience and that of a few "friends." Perceptions differ widely among robbers, because each observes only a small fraction of the actions taken by the system." (p. 225)

5.1. An economic model of networks and crime that includes social learning

Consider a network of n delinquents. We keep track of social connections in a delinquency network \mathbf{g} through its *adjacency matrix* $\mathbf{G} = [g_{ij}]$, where $g_{ij} = 1$ if i and j are linked to each other (for example, they may be co-offenders or friends) and $g_{ij} = 0$, otherwise. We set $g_{ii} = 0$. The network is undirected so that if $g_{ij} = 1$, then $g_{ji} = 1$.

Delinquents decide how much criminal effort to exert in order to maximize their own utility. The effort level of delinquent i is denoted by, y_i , and $\mathbf{y} = (y_1, y_2, \dots, y_n)^T$ represents the population delinquency profile in network \mathbf{g} . Each agent i selects an effort $y_i \geq 0$, and obtains a utility payoff $u_i(\mathbf{y}, \mathbf{g})$ that depends on the effort profile \mathbf{y} and on the underlying network \mathbf{g} , in the following way:

$$u_i(\mathbf{y}, \mathbf{g}) = \underbrace{(a_i + \eta)y_i}_{\text{benefits}} - \underbrace{\frac{1}{2} y_i^2}_{\text{cost}} + \underbrace{\theta \sum_{j=1}^n g_{ij} y_i y_j}_{\text{social learning}}, \quad (1)$$

where $\theta > 0$.

The proceeds from crime are given by $(a_i + \eta)y_i$ and are increasing in own effort y_i , where a_i denotes differences in agents' criminal productivity (e.g. age, gender, or education). Productive characteristics that are shared by all members of the network are given by η (e.g. network size, the prosperity level of the neighborhood, the local clearance rate, etc.). The cost of committing crime is given by the term $\frac{1}{2} y_i^2$, which increases with own effort y_i , as the severity of the punishment and the probability of getting caught both increase with one's involvement in crime.

The new element in this utility function is the social interaction term $\theta \sum_{j=1}^n g_{ij} y_i y_j$, which reflects the influence of an individual's friends' behavior on his or her own actions. This last term captures the general idea of Sutherland (1947) that delinquents learn from each other how best to commit crime (i.e. they learn the technology of crime). They may also learn how to rationalize or justify the fact that they are committing a crime (i.e. they learn a norm or gain status from committing crime). In this model, social interactions take the form of social learning.

Importantly, this new social factor is formulated as the *sum* of agent i 's friends' crimes, as such, this model is typically called the *local aggregate model* (where the term "local" refers to the local neighborhood of agent i , i.e. all agents j that i is directly linked with). Know-how is collected from criminal friends. It increases with the number of delinquent friends and with the level of their friends' involvement in crime. Technically, one can show that: $\frac{\partial^2 u_i(\mathbf{y}, \mathbf{g})}{\partial y_i \partial y_j} = \theta g_{ij} \geq 0$, which means that crime decisions are *complements*. I derive more utility from committing crime when my friends commit more crime and vice-versa.

In the economic model, each delinquent i chooses his own crime level, y_i , in order to maximize his own utility, which is given by equation (1). For any network structure, we can solve for the Nash equilibrium of this utility maximization problem. The first-order condition for each i is given by:

$$y_i = a_i + \eta + \theta \sum_{j=1}^n g_{ij} y_j. \quad (2)$$

In equilibrium, the population wide crime profile, \mathbf{y}^* , can be written as:

$$\mathbf{y}^* = \sum_{k=0}^{\infty} \theta^k \mathbf{G}^k \boldsymbol{\alpha}, \quad (2a)$$

where $\boldsymbol{\alpha}$ is a vector containing all $\alpha_i = a_i + \eta$ and where, $\sum_{k=0}^{\infty} \theta^k \mathbf{G}^k \boldsymbol{\alpha}$, is the weighted *Katz-Bonacich centrality* of each agent, which is constructed as the sum of all walks between agent i and all $j \in \{1, \dots, n\}$ of length 0 to k . Each walk of length k is weighted by θ^k . This number is then multiplied by α_i . Thus, the amount of crime individual i will commit in equilibrium is determined by (i) his productive characteristics, a_i , (ii) factors that are shared by all network members, η , and (importantly!) (iii) by individual i 's Katz-Bonacich centrality.

In Sections 3 and 4, we argued that network centrality mattered. Here, we see that this important idea can be derived directly from a utility maximizing model of networks and crime. Also, as we shall discuss in more detail below, the specific definition of centrality that matters most for policy will depend on the specific problem in hand and the specific model that the researcher writes down. In the simple, local aggregate model of crime, for example, it is weighted Katz-Bonacich centrality that matters (as opposed to degree centrality, betweenness centrality, or some other measure of centrality).

In the local aggregate model of crime defined by equations (1) and (2), the interdependence of network payoffs is restricted to the local network comprised of all j who are directly linked to i . But since local networks of direct links overlap, the payoff interdependence spreads through the entire network. In equilibrium, the effects of individual i 's decisions travel along all existing network paths and affect the decisions made by all j either directly or indirectly. Katz-Bonacich centrality measures the total effect that agent i 's decisions have on all other agents in the network.

In the standard Beckerian model of crime, uniformly raising the punishment costs borne by delinquents shifts crime down; both the average and the aggregate delinquency level decreases.

This homogeneous policy tackles average behavior explicitly and does not discriminate among delinquents depending on their relative contribution to the aggregate delinquency level.

In the network crime model outlined above, there is a non-uniform distribution of delinquency efforts across the network. This distribution reflects the variance of network (Katz-Bonacich) centralities of different delinquents. In this situation, a targeted policy that discriminates among delinquents depending on their relative network location alters the entire distribution of delinquency efforts, as opposed to just shifting it up or down. Importantly, a milder but more selective policy can (in principle) yield a larger reduction in aggregate delinquency than a standard policy applied uniformly to all agents. In practice, the planner may want to identify optimal network targets to concentrate (scarce) investigatory resources on some particular individuals, or to isolate them from the rest of the group, either through leniency programs, social assistance, after school programs, or incarceration.

Lesson #7 *In the local aggregate model of crime, policy measures targeted at more central individuals may lower crime in a more efficient manner than the standard Beccarian policy of harsher punishments for all.*

5.1.1. The key player policy

In the context of the economic model of networks and crime, the *key player* is defined as the one that if removed from the network induces the largest reduction in aggregate delinquency. Given that delinquent removal has both a direct and an indirect effect on the group outcome, the choice of the key player results from a tradeoff between both effects. In particular, the key player need not necessarily be the one exerting the highest delinquency effort or, equivalently, the one with the

highest centrality measure. The planner's objective is thus to generate the highest possible reduction in aggregate delinquency level by picking the appropriate delinquent.

Formally, the planner solves the following problem: $\max_i \{y^*(\mathbf{g}) - y^*(\mathbf{g}^{-i})\}$, where $y^*(\mathbf{g}) = \sum_{i=1}^n y_i^*$ is the total criminal effort in the network at the Nash equilibrium and $y^*(\mathbf{g}^{-i})$ is the total criminal effort in the network after the removal of delinquent i . Ballester et al. (2006, 2010) provide a new centrality measure for each individual i , denoted by c_i , referred to as the *intercentrality measure*, that defines key players. So, we can rank each individual in the network in terms of their intercentrality measure c_i so that the delinquent with the highest c_i will reduce total crime the most if removed from the network, the delinquent with the second highest c_i will be the next one who reduce total crime the most if removed from the network, etc.

More generally, the key player policy is such that the planner perturbs the network by removing a delinquent and all other delinquents are allowed to change their effort after the removal but the network is not “rewired”, i.e., individuals do not optimally change their relationships (links) with their friends after the removal of the key player. Thus, the total long-run effect of such a policy will depend, in part, how costly it is for delinquents to find and form new links.

Lesson #8 *In the economic model of networks and crime that includes social learning, targeting high intercentrality individuals will always lower crime by at least as much or by more than targeting individuals with high degree centrality, betweenness centrality, eigenvector centrality, or other measure of centrality.*

5.2. An economic model of networks and crime that includes social norms

The local aggregate model is a model of social learning. Another important social mechanism could be that of (anti)conformist behavior in the presence of social norms. Patacchini and Zenou (2012), Liu et al. (2014), Blume et al. (2015), Boucher (2016), and Ushchev and Zenou (2018) have all studied an alternative model to the one given in (1) where social norms matter. The utility function is now given by:

$$u_i(\mathbf{y}, \mathbf{g}) = \underbrace{(\hat{a}_i + \hat{\eta})y_i}_{\text{benefits}} - \underbrace{\frac{1}{2} y_i^2}_{\text{cost}} - \underbrace{\hat{\theta}(y_i - \bar{y}_i)^2}_{\text{social norm}}, \quad (3)$$

where $\bar{y}_i = \frac{\sum_{j=1}^n g_{ij} y_j}{d_i}$ is the social norm faced by individual i and d_i is the degree (i.e., the number of direct links) of i . The main difference with the previous model is the social interaction term of the utility function. Indeed, in the model whose utility is given by (1), referred to as the local-aggregate model, the sum of criminal efforts positively affects the utility of delinquent i . In the model whose utility is given by (3), referred to as the *local-average model*, each individual i suffers a utility reduction equal to $\hat{\theta}(y_i - \bar{y}_i)^2$ from failing to conform to others. In other words, there is a peer-group pressure faced by delinquent i , who seeks to minimize her social distance from her reference group.

In this model, the network interpretation is very different from that of the local-aggregate model, where we interpret connections as a transfer of know-how about crime between delinquents. In the local-average model, it is social pressure that matters: if my direct connections are, on average, committing a certain level of crime, then it is costly for me not to *conform* to this crime level. In particular, the crime effort level of my direct neighbors does not always positively affects me. Indeed, if i and j are connected, then, in the local aggregate model, $\frac{\partial u_i(\mathbf{y}, \mathbf{g})}{\partial y_j} > 0$, since the more

criminally active is a direct connection, the higher is i 's utility of committing crime. This is not always true in the local-average model since $\frac{\partial u_i(\mathbf{y}, \mathbf{g})}{\partial y_j} \gtrless 0 \Leftrightarrow y_i \gtrless \bar{y}_i$. In words, when delinquent j makes effort y_j , she exerts a positive (negative) externality on her direct neighbor i if and only if the effort of i is above (below) i 's social norm. Indeed, if i 's effort is above (below) her social norm \bar{y}_i , then, when a neighbor j increases her effort $y_j \in \bar{y}_i$, the social norm \bar{y}_i increases, which, in turn, increases (decreases) i 's utility because y_i is now closer to (further away from) \bar{y}_i , i.e., $y_i - \bar{y}_i$ becomes smaller (greater). This is why in the local-aggregate model, θ is interpreted as the *social multiplier* while, in the local-average model, $\hat{\theta}$ is viewed as the *taste for conformity*.

Interestingly, even though the utility function and thus the preferences of the agents are very different, the two models have very similar criminal behaviors. Indeed, in the local-aggregate model, the criminal effort of each delinquent is given by (2), while, after some renormalizations $\left(a_i + \eta = \frac{\hat{a}_i + \hat{\eta}}{1 + 2\hat{\theta}}, \theta = \frac{2\hat{\theta}}{1 + 2\hat{\theta}}\right)$, in the local-average model, it is equal to:

$$y_i = a_i + \eta + \theta \sum_{j=1}^n \hat{g}_{ij} y_j, \quad (4)$$

where $\hat{g}_{ij} = \frac{\sum_{j=1}^n g_{ij}}{d_i}$. In other words, the only difference between (2) and (4) is that, in the latter, the adjacency matrix of direct connection is row-normalized (i.e. the sum of each row is equal to 1) while, in the former, it is not the case since the sum of each row is just the number of connections of each individual.

In the local-aggregate model, the main determinant of individual crime is the weighted Katz-Bonacich centrality of each delinquent, in which the weights are given by her $\alpha_i \equiv a_i + \eta$.

In other words, both her position in the network and her observable and unobservable characteristics matter in explaining her criminal activities.

In the local-average model, an individual's position in the network is less important.¹¹ What matters is α_i . Usually, delinquents with high α_i (criminal ability) commit more crime and thus exert effort above their social norm. The delinquents with low α_i linked to these delinquents exert more crime effort than what their ability will predict because they want to be socially close to their social norm, which is affected by the criminal with high ability. Moreover, as pointed out by Ushchev and Zenou (2018), the policy implications of these two models are very different and help highlight the debate between group-based versus individual-based policies.

As shown in Section 5.2, if the utility function includes social learning as in equation (1), then the optimal policy for reducing crime is to target key players (Ballester et al., 2006; Lindquist and Zenou, 2014; Zenou, 2016; Liu et al., 2018). The removal of key players can have large effects on crime because of the feedback effects or “social multipliers” at work. In other words, as the proportion of individuals participating in criminal behavior increases, the impact on others is multiplied through social networks. Thus, behavior (either good or bad) can be amplified, and interventions can become more effective.

In large groups, a key-player policy would have nearly no effect in the local-average model, since it would not affect the social norm that committing crime is morally wrong. To be effective, one would have to change the social norm for each of the criminals, which is clearly a more difficult objective. In that case, it is necessary to target a *group* or gang of criminals to reduce crime drastically. This illustrates the fact that, for the local-aggregate model, *individual-based policies*

¹¹ For example, if all individuals have the same α , in the local-average model, they will all commit the same crime effort, independently of their position in the network while, in the local-aggregate model, their effort will be proportional to their position (in terms of Katz-Bonacich centrality) in the network so that more central delinquents exert higher crime effort than less central ones.

are more appropriate while, for the local-average model, *group-based policies* are more effective.¹²

In small groups, one could still target high crime (α_i) individuals, since removing them would have a large impact on the group norm when the group size is small.

Lesson #9 *If conforming to the social norm is the main social mechanism, then group-based policies should be applied to large groups, since targeting individuals will not change the social norm. In small groups, one can change the social norm by targeting high crime individuals, regardless of their position in the structure of the network.*

5.2.1. Different social norms

The utility function of an individual in the local-average model is given by (3). The key element of this function is the social norm, defined as $\bar{y}_i = \frac{\sum_{j=1}^n g_{ij} y_j}{d_i} = \sum_{j=1}^n \hat{g}_{ij} y_j$. This is the standard model of peer effects that most researchers have in mind. Estimating these peer effects is typically done using an empirical model similar to (4). In doing so, we are making a strong assumption. We are assuming that the social norm facing each individual is the average behavior of their closest neighbors. For example, in crime, we are testing the impact of the average crime rate in the neighborhood of agent i on agent i 's individual crime rate. But what if this agent's social norm is determined by a single role model? For example, what if he or she is primarily influenced by the gang leader or by some other high profile figure whose crime level differs from the average?

To address this potentially important idea, Rendall et al. (2019) consider the same utility function as in (4) but replace the standard expression for the social norm with the following

¹² For recent overviews on individual versus place-based policies, see Kline and Moretti (2014) and Neumark and Simpson (2015).

geometric sum: $\bar{y}_i = \left(\sum_{j=1}^n \hat{g}_{ij} y_j^\rho \right)^{1/\rho}$, with $-\infty \leq \rho \leq +\infty$. When $\rho = 1$, we are back in the standard local-average model. When $\rho \rightarrow +\infty$, then $\bar{y}_i = \max_j y_j$, so that only the crime leader's behavior matters. When $\rho \rightarrow -\infty$, then $\bar{y}_i = \min_j y_j$, so that each individual compares himself with the individual with the lowest crime level. Which social norm matters in real life is clearly an empirical question. Identifying these “bad apples” or “shining stars” or other types of influential role models could, of course, aid in fighting delinquent behavior and crime, since they act as “key influencers”.¹³

5.3 A hybrid model

The local aggregate model includes a social interaction term representing social learning. The local average model includes a social interaction term representing conformist behavior in the presence of a social norm. As we saw above, distinguishing between these two types of mechanisms becomes important for designing the optimal policy response. However, nothing precludes us from including both mechanisms in our model of networks and crime. In fact, this has been done in Liu et al. (2014). They show how the intercentrality measure (defined in Section 5.1.1.) can be derived from such a hybrid model; giving us (once again) a micro-founded measure for identifying key players in network applications.

5.4. Extending the key player policy to more than one activity

So far, we have assumed that each individual only takes part in one activity: crime. In reality, individuals make a multitude of choices, many of which are interdependent. As a result, peers

¹³ For example, Diaz et al. (2018) show that the social distance to a criminal leader has a strong impact on the criminal behavior of adolescents in the U.S.

can have multiple and sometimes opposing influences on their friends. Following Chen et al. (2018), we can extend the economic model of networks and crime to include multiple activities. These activities can be complements (e.g. committing crime and consuming drugs) or substitutes (e.g. crime and education). Within each activity we assume that there are local network externalities amongst neighbors.

Let us first consider a version of the local aggregate model in which individuals in one activity (say crime) are somewhat different and belong to a somewhat different network than individuals from the other activity (say education). In this new model, there are two beneficial effects of removing a criminal from the network. First, there are fewer spillovers in crime so that the neighbors of the removed person exert less crime effort; which, in turn, induces their neighbors to reduce their crime effort, and so on. Second, by reducing crime the planner induces the remaining criminals to increase their education effort; which, because of spillovers in education, induces their neighbours to also study more, and so forth. As a result, there is a virtuous effect of removing a criminal since it induces the remaining criminals to commit less crime and to focus more on education.

Consider now crime and drug consumption (complementary activities). When a criminal is removed from the network, the remaining criminals reduce their crime effort and, because of complementarity between activities, also reduce their drug consumption. There is again a virtuous effect of removing a criminal in a network, which is not taken into account in the single activity case. This is why the key player in the single activity case can be different from the key player in the two-activity case.

In the local-average model with two activities, there may arise a conflict between the desire to conform to two different and potentially opposing social norms. It will be costly for individual i to deviate both from her friends' average crime effort and from her friends' average education effort.

The solution to this problem depends on the different α_i s, which may be different between distinct activities. For example, if agent i has some initial advantage in crime (higher ability α_i), then she will follow the social norm in crime imposed by her friends more closely than the norm in education, because she has a relatively higher return from crime than from education.

An important advantage of the economic approach to networks and crime is that it allows us to model multiple activities in a hybrid model that includes more than one social mechanism. The intercentrality measure can then be derived from this model.

Lesson #10 *When designing anti-delinquency policies in schools, policy makers should model educational effort and delinquent behaviour jointly, and then derive the appropriate intercentrality measure. The intercentrality measure can be used to help design targeted policies for promoting educational effort and reducing delinquent behavior.*

5.5. Challenges facing the economic model of networks and crime

We conclude our presentation of the economic model of networks and crime with a discussion of some of the practical challenges facing researchers and policy makers interested in applying the lessons we have learned above to solve real-world problems. The first challenge is that of measurement error in crime network data. Collecting data and mapping out criminal networks is clearly more problematic, costly, and time consuming than mapping out (for example) a network of co-authorships among economists.¹⁴ While most authors are trying to make their work as visible

¹⁴ See de Paula et al. (2019) who provide results on the identification of social networks from observational panel data that contains *no information* on social ties between agents. See, also, Breza et al. (2019) who propose an inexpensive and feasible strategy for network elicitation using Aggregated Relational Data (ARD) – responses to questions of the form “how many of your links have trait k ?” Their method uses ARD to recover parameters of a network formation model, which permits the estimation of any arbitrary node- or graph-level statistic. ARD is considerably cheaper to obtain than full or even partial-network data.

as possible, most criminals are trying to hide their illegal activities from the police. Network analysts need to consider the consequences (for their policy recommendations) of the fact that network links in co-offending may be missing in a non-random fashion. Importantly, Chandrasekhar and Lewis (2016) demonstrate that non-classical measurement error will arise even when nodes are missing at random and that this measurement error leads to inconsistent estimates of network effects and measures of network statistics (such as centrality).

Even with high quality network data in hand, estimating the types of behavioral peer effects models that we have outlined above is itself a difficult task. Purely structural measures of networks centrality (such as degree or betweenness) can be readily calculated once the necessary data is available. In contrast to this, behavioral measures of network centrality (such as the intercentrality measure) require the estimation of causal peer effects and the ability to separate between exogenous and endogenous peer effects (Manski 1993). Aside from this, researchers must also deal with a variety of empirical issues such as (i) correlated effects, (ii) endogenous network formation (selection), and (iii) the simultaneity of peer actions and outcomes.¹⁵

It is also important to keep in mind that in our discussion of the economic model of networks and crime, we maintained the assumption of a fixed network. We did not allow the network to “re-wire” once a key player was removed. We did not allow the key player’s former co-offenders the opportunity to form new links between each other or with new co-offenders. If a key player can be rapidly replaced at a low cost, then the structure of the network will not change much. This type of re-wiring lowers the overall advantage of targeting specific individuals as opposed to simply focusing on the most active criminal.

¹⁵ See Graham (2015) and Boucher and Fortin (2016) for overviews on identifying causal peer effects.

The importance of re-wiring, however, will clearly depend on the context and the structure of the network under study. Morselli and Roy (2008), Zhang and Chin (2002), and Zhang (2014) all argue that they study key brokers with unique skills and resources that are not easily replaced in the short- or even medium-run. Thus, the removal of these brokers results in significant and long-lasting reductions in crime. In contrast to this, Frank Nitti was able to step into the leadership role of the Chicago Mafia after the arrest of Al Capone. After which, the Chicago Mafia continued to expand and prosper. In other contexts, such as Boston's Operation Ceasefire program, the police were not looking for people to remove, but rather for key actors and gangs whom they could inform of their new policies regarding gang violence.¹⁶

6. Big data and computer technology

While the economic approach to networks and crime faces several unique challenges, a more general set of challenges and opportunities has arisen along with the growing availability of big data and with the development of computer technology. Our own work (Lindquist and Zenou 2014) shows how large (population) data sets with information on co-offenses can be used to map out criminal networks and to identify key players or groups. Many of the networks ideas and techniques that economists use today are borrowed from computer science (and other disciplines). Today, computer scientists are working hard to make these ideas and techniques more accessible (automated) to law enforcement agencies. Their goal is to provide network information in real time in order to provide practical information for crime prevention and criminal investigations.

¹⁶ Another possibility is that crime could go up after the removal of a key player if a power struggle ensues among the remaining members of the network or if a competing network uses the opportunity to try and increase their market share of illegal activities. Furthermore, if followers are more inclined to commit violence than leaders, then violence can increase when the restraining hand of the leader is removed (Rigterink 2019).

The “first generation” of police network tools can be characterized by our favorite detective who we opened this article with. She used pen and paper network mapping techniques. Xu and Chen (2005) describe the “second generation” of network and crime tools as graphic software that allows the police to map out and visualize larger quantities of network data. Examples of this type of network software include Analyst’s Notebook, which has been used by various police forces in the U.S., U.K., and the Netherlands, and NetMap, which has been used (for example) in the FinCEN system at the U.S. Department of the Treasury to analyze financial transactions data to detect money laundering (see Goldberger and Senator 1998).

One drawback of this type of software is that they typically rely on a very labor intensive data input process (Seidler and Adderly 2013). Commercial software (such as COPLINK) are currently addressing this (and related issues) for the U.S. and our own experience leads us to believe that this problem can be solved in countries that already use national crime report and arrest databases.

Xu and Chen (2005) present their own software, CrimeNet Explorer, which they call the “third generation” of network and crime tools. They present a tool that allows law enforcement authorities to extract and analyze network data from large criminal justice databases. They propose a method for automated network analysis and visualization, which takes several steps: (i) network creation, (ii) network partitioning, (iii) structural analysis, and (iv) network visualization. Their software automatically detects subgroups from a network, identifies central members, and extracting interaction patterns between subgroups.

Tayebi and Glässer (2011) have also developed a set of computerized community detection methods. Their program can identify communities at one point in time and also trace out the evolution of these communities over time, i.e. they implement evolutionary clustering methods as well. They demonstrate these methods using five years of real-world arrest data from the Canadian

Province of British Columbia. These data are based on crime reports, and each crime report includes information on the crime incident including the identities of the crime suspects. An interesting aspect of their work is that they do not just identify groups of co-offenders, but they also try to identify organized crime groups. They do this by defining organized crime groups as offender groups that commit serious crime and that persist over time.

While it is certainly tempting for academics (like ourselves) to be enamored with all of this new network and crime analysis software, it is not clear that these tools are actually used by law enforcement analysts when available, nor helpful when used. In fact, Seidler and Adderly (2013) argue that these types of network tools “rarely produce immediately applicable intelligence products” (p. 323). They argue that there is, in fact, a growing need for network analysis to help make sense of the ever growing mountain of law enforcement data. But, at the same time, network analysis needs to be integrated into the police’s own intelligence routines and cycles. Furthermore, they stress that police force priorities need to be used when deciding on who is “key” or central in a network. These priorities are not included in the structural measures of centrality (such as betweenness) that are typically report by this type of software, and hence, rarely used in practice. One strength of the economic approach to networks and crime is that it allows us to include police priorities in the model and then derive efficient policy and centrality measure given these priorities.

7. Conclusion

In this article, we illustrate how social network analysis can be used to help understand more about the root causes of delinquent behavior and crime and to provide practical guidance for the design of crime prevention policies. We give several examples of how such tools could potentially be used by practitioners. We also describe examples of how such policies have been successfully used in

the field, e.g. Boston's Operation Ceasefire (Kennedy et al. 1997, Kennedy et al. 2001, Braga et al. 2001).

Alongside the growing awareness of the potential of social networks to inform police policy, there has been a rapid growth in the amount of data available to law enforcement agencies and to researchers. Computer scientists and network specialists are providing new and better computer software to aid in the analysis of this data. However, some observers have argued that such software focuses too heavily on delivering structural network statistics that do not reflect the operational priorities of the police (Seidler and Adderly 2013). We would argue, that such structural network statistics are many times lacking in behavioral content as well.

The economic approach to networks and crime may help remedy these problems. It has the potential to provide new insights and tools that can be used to curb delinquency, crime and other anti-social behaviors. In a nutshell, the economic approach amounts to writing down an accurate model of the problem in hand and then deriving the optimal policy from this model. In essence, we want to model behavior, the choices people make, and the social mechanisms that affect those choices, so that we can better understand the root causes of crime and, hence, design better policies to lower crime. For example, we have discussed why Ballester et al.'s (2006, 2010) intercentrality measure is an appropriate measure of network centrality for use in focused deterrence strategies. Importantly, the police's own operational priorities could readily be included in such a modeling framework.

Our vision is that this type of theoretical discussion and modeling exercise could be included in the initial problem analysis stage of the design of new policies; in the same way that Kennedy et al. (1997) were involved in the design of Boston's Operation Ceasefire program. Our own work (Lindquist and Zenou 2014) also demonstrates how these techniques can be used together with big

data to identify key players in real world co-offending networks. Such techniques could be integrated into network software for use by the police.

However, our discussion above also leads us to conclude that the role of the analyst cannot be completely automated. Before deriving an appropriate policy, an analyst must first determine the key features of the problem in hand. What are the underlying social mechanisms? Should we consider multiple activities and/or multiplex networks? This will most likely need to be done together with various experts and practitioners in a group-audit type of setting. We also feel that future work should focus on providing credible empirical evidence concerning the strengths and weaknesses of the network approach to fighting crime.

References

- Ballester, Coralio, Antoni Calvó-Armengol, and Yves Zenou (2006) "Who's Who in Networks. Wanted: The Key Player," *Econometrica* 74(5), 1403-1417.
- Ballester, Coralio, Antoni Calvó-Armengol, and Yves Zenou (2010) "Delinquent Networks," *Journal of the European Economic Association* 8(1), 34-61.
- Bayer, Patrick, Randi Hjalmarsson, and David Pozen (2009) "Building Criminal Capital Behind Bars: Peer Effects in Juvenile Corrections," *Quarterly Journal of Economics* 124(1), 105-147.
- Beccaria, Cesare (1764) *On Crimes and Punishment*.
- Becker, Gary S. (1968) "Crime and Punishment: An Economic Approach," *Journal of Political Economy* 76(2), 169-217.
- Bentham, Jeremy (1789) *An Introduction to the Principles of Morals and Legislation*.
- Bentham, Jeremy (1811) *Punishments and Rewards*.
- Bernasco, W., de Graaff, Th., Rouwendal, J. and W. Steenbeek (2017), "Social interactions and crime revisited: An investigation using individual offender data in Dutch neighborhoods," *Review of Economics and Statistics* 99, 622--636.
- Bhuller, Manudeep, Gordon B. Dahl, Katrine V. Løken and Magne Mogstad (2018) "Incarceration Spillovers in Criminal and Family Networks," NBER Working Paper No. 24878.
- Bichler, Gisela and Aili E. Malm (Editors) (2015) *Disrupting Criminal Networks: Network Analysis in Crime Prevention*, Boulder: First Forum Press, Lynne Rienner Publishers, Inc.
- Blume, Lawrence E., Brock, William A., Durlauf, Steven N. and Rajshri Jayaraman (2015), "Linear social interactions models," *Journal of Political Economy* 123, 444--496.
- Bonacich, Phillip (1987) "Power and Centrality: A Family of Measures," *American Journal of Sociology* 92(5), 1170-1182.
- Borgatti, Stephen P. (2006) "Identifying Sets of Key Players in a Social Network," *Computational & Mathematical Organizational Theory* 12(1), 21-34.
- Boucher, Vincent (2016), "Conformism and self-selection in social networks," *Journal of Public Economics* 136, 30-44.
- Boucher, Vincent and Bernard Fortin (2016), "Some challenges in the empirics of the effects of networks," In: Bramoullé, Yann, Andrea Galeotti and Brian Rogers, *The Oxford Handbook on the Economics of Networks*, Oxford: Oxford University Press.

Braga, Anthony A., Kennedy, D.M., Waring, E.J. and A.M. Piehl (2001), "Problem oriented policing, deterrence, and youth violence: An evaluation of Boston's Operation Ceasefire," *Journal of Research in Crime and Delinquency* 38, 195-225.

Breza, Emily, L., Chandrasekhar, Arun, McCormick, Tyler and Mengjie Pan (2019), "'Using aggregated relational data to feasibly identify network structure without network data,'" Unpublished manuscript, Harvard University.

Braga, Anthony A., David Weisburd and Brandon Turchan (2018) "Focused Deterrence Strategies and Crime Control: An Updated Systematic Review and Meta-Analysis of the Empirical Evidence," *Criminology & Public Policy* 17(1), 205-250.

Bright, David A. (2015) "Identifying Key Actors in Drug Trafficking Networks," in Gisela Bichler and Aili E. Malm (Editors) *Disrupting Criminal Networks: Network Analysis in Crime Prevention*, Boulder: First Forum Press, Lynne Rienner Publishers, Inc., 67-88.

Burt, Ronald S. (1992) *Structural Holes: The Social Structure of Competition*, Cambridge: Harvard University Press.

Burt, Ronald S. (2005) *Brokerage and Closure: An Introduction to Social Capital*, Oxford: Oxford University Press.

Calderoni, Francesco (2015) "Predicting Organized Crime Leaders," in Gisela Bichler and Aili E. Malm (Editors) *Disrupting Criminal Networks: Network Analysis in Crime Prevention*, Boulder: First Forum Press, Lynne Rienner Publishers, Inc., 89-110.

Calvó-Armengol, Antoni and Yves Zenou (2004) "Social Networks and Crime Decisions. The Role of Social Structure in Facilitating Delinquent Behavior," *International Economic Review* 45(3), 939-958.

Chandrasekhar, Arun G. and Randall Lewis (2016) "Econometrics of Sampled Networks," unpublished manuscript, Stanford University.

Chen, Ying-Ju, Zenou, Yves and Junjie Zhou (2018), "Multiple activities in networks," *American Economic Journal: Microeconomics* 10(3), 34-85.

Cook, Philip J. (1980) "Research in Criminal Deterrence: Laying the Groundwork for the Second Decade," *Crime and Justice* 2, 211-268.

Corno, Lucia (2017) "Homelessness and crime: Do your friends matter? *The Economic Journal* 127(602), 959-995.

Damm, Anna P. and Christian Dustmann (2014) "Do Young People Learn Criminal Behavior? Quasi-Experimental Evidence," *American Economic Review* 104(6), 1806-1832.

de Paula, Aureo, Rasul, Imran and Pedro CL Souza (2019), “Recovering Social Networks from Panel Data: Identification, Simulations and an Application,” Unpublished manuscript, University College London.

Diaz, Carlos, Patacchini, Eleonora, Verdier, Thierry and Yves Zenou (2018), “Leaders in Juvenile Crime,” CEPR Discussion Paper No. 13120.

Drago Francesco and Roberto Galbiati (2012) “Indirect Effects of a Policy Altering Criminal Behavior: Evidence from the Italian Prison Experiment,” *American Economic Journal: Applied Economics* 4(2), 199-218.

Dustmann, Christian and Rasmus LandersØ (2018) “Child’s Gender, Young Fathers’ Crime, and Spillover Effects in Criminal Behavior,” CReAM Discussion Paper Series 05/18.

Eriksson, Karin Hederos, Randi Hjalmarsson, Matthew J. Lindquist, and Anna Sandberg (2016) “The Importance of Family Background and Neighborhood Effects as Determinants of Crime,” *Journal of Population Economics* 29(1), 219-262.

Glaeser, Edward, Bruce Sacerdote, and José A. Scheinkman (1996) “Crime and Social Interactions,” *Quarterly Journal of Economics* 111(2), 507-548.

Goldberg, H.G. and T.E. Senator (1998), “Restructuring databases for knowledge discovery by consolidation and link formation,” In: *Proceedings of 1998 AAAI Fall Symposium on Artificial Intelligence and Link Analysis*, Menlo Park, CA: AAAI Press.

Gould, Roger V. and Roberto M. Fernandez (1989) “Structures of Mediation: A Formal Approach to Brokerage in Transaction Networks,” *Sociological Methodology* 19, 89-126.

Graham, Bryan S. (2015), “Methods of identification in social networks,” *Annual Review of Economics* 7, 465-485.

Haynie, Dana L. (2001) “Delinquent Peers Revisited: Does Network Structure Matter?” *American Journal of Sociology* 106(4), 1013-1057.

Heller, Sara B., Shah, Anuj K., Guryan, Jonathan, Ludwig, Jens, Mullainathan, Sendhil and Harold A. Pollack (2017), “Thinking, Fast and Slow? Some Field Experiments to Reduce Crime and Dropout in Chicago,” *Quarterly Journal of Economics* 132(1), 1-54.

Hjalmarsson, Randi, Helena Holmlund, and Matthew J. Lindquist (2015) “The Effect of Education on Criminal Convictions and Incarceration: Causal Evidence from Micro-data,” *Economic Journal* 125(587), 1290-1326.

Hjalmarsson, Randi and Matthew J. Lindquist (2012), “Like Godfather, Like Son: Exploring the Intergenerational Nature of Crime,” *Journal of Human Resources* 47, 550-582.

Hjalmarsson, Randi and Matthew J. Lindquist (2013), “The Origins of Intergenerational Associations in Crime: Lessons from Swedish adoption data,” *Labour Economics* 20, 68-81.

Hjalmarsson, Randi and Matthew J. Lindquist (2019) "The Causal Effect of Military Conscription on Crime," forthcoming in *The Economic Journal*.

Jackson, Matthew O. (2008) *Social and Economic Networks*, Princeton: Princeton University Press.

Jackson, Matthew O., Rogers, Brian and Yves Zenou (2017), "The Economic Consequences of Social Network Structure," *Journal of Economic Literature* 55, 49-95.

Katz, Leo (1953) "A New Status Index Derived from Sociometric Analysis," *Psychometrika* 18(1), 39-43.

Kennedy, D.M., Braga, A.A. and A.M. Piehl (1997), "The (Un)Known Universe: Mapping Gangs and Gang Violence in Boston," In: D. Weisburd and T. McEwen (Eds.), *Crime Mapping and Crime Prevention*, Monsey, N.Y: Criminal Justice Press.

Kennedy, D.M., Braga, A.A., Piehl, A.M. and E.J. Waring (2001), *Reducing Gun Violence: The Boston Gun Project's Operation Ceasefire*, Washington, D.C: U.S. National Institute of Justice.

Kling, Jeffrey R., Ludwig, Jens and Lawrence F. Katz (2005), "Neighborhood Effects on Crime for Female and Male Youth: Evidence from a Randomized Housing Voucher Experiment," *Quarterly Journal of Economics* 120(1), 87-130.

Klein, Malcom W. (1971), *Street Gangs and Street Workers*, Englewood Cliffs, NJ: Prentice-Hall.

Klein, Malcom W. (1995), *The American Street Gang*, New York: Oxford University Press.

Kline, Patrick and Enrico Moretti (2014) "People, Places, and Public Policy: Some Simple Welfare Economics of Local Economic Development Programs," *Annual Review of Economics* 6, 629-662.

Lindquist, Matthew J. and Yves Zenou (2014), "Key Players in Co-Offending Networks", CEPR Discussion Paper No. 9889.

Liu, Xiaodong, Patacchini, Eleonora and Yves Zenou (2014), "Endogenous Peer Effects: Local Aggregate or Local Average?" *Journal of Economic Behavior and Organization* 103, 39-59.

Liu, Xiaodong, Eleonora Patacchini, Yves Zenou, and Lung-Fei Lee (2018), "Who is the Key Player? A Network Analysis of Juvenile Delinquency," Unpublished manuscript, Monash University.

Ludwig, Jens, Duncan, Greg J. and Paul Hirschfield (2001), "Urban Poverty and Juvenile Crime: Evidence from a Randomized Housing-Mobility Experiment," *Quarterly Journal of Economics* 116(2), 655-679.

Manski, Charles F. (1993) "Identification of Endogenous Social Effects: The Reflection Problem," *The Review of Economic Studies* 60(3), 531-542.

Mastrobuoni, Giovanni (2015) "The Value of Connections: Evidence from the Italian-American Mafia," *The Economic Journal* 125(586), 256-288

Mastrobuoni, Giovanni and Eleonora Patacchini (2012), "Organized Crime Networks: An Application of Network Analysis Techniques to the American Mafia," *Review of Network Economics* 11(3), Article 10.

McGloin, Jean Marie (2005) "Policy and Intervention Considerations of a Network Analysis of Street Gangs," *Criminology & Public Policy* 4(3), 607-636.

McGloin, Jean Marie (2007) "The Organizational Structure of Street Gangs in Newark, New Jersey: A Network Analysis Methodology," *Journal of Gang Research* 15(1), 1-34.

McGloin, Jean Marie and Holly Nguyen (2014) "The Importance of Studying Co-offending Networks for Criminological Theory and Policy," in Carlo Morselli (Editor) *Crime and Networks*, New York: Routledge, Taylor & Francis, 13-27.

Morselli, Carlo (Editor) (2014), *Crime and Networks*, New York: Routledge, Taylor & Francis, 13-27.

Morselli, Carlo and Julie Roy (2008), "Brokerage Qualifications in Ringing Operations," *Criminology* 46(1), 71-98.

Murphy, Francis X. (2019), "Does Increased Exposure to Peers with Adverse Characteristics Reduce Workplace Performance? Evidence from a Natural Experiment in the US Army," *Journal of Labor Economics* 37(2), 435-466.

Neumark, David and Helen Simpson (2015), "Place-based policies," In: Duranton, G., Henderson, V., and Strange, W. (Eds.), *Handbook of Regional and Urban Economics, Vol. 5B*, Amsterdam: Elsevier Publisher, pp. 1197-1288.

Papachristos, Andrew V. (2009), "Murder by Structure: Dominance Relations and the Social Structure of Gang Homicide," *American Journal of Sociology* 115(1), 74-128.

Patacchini, Eleonora and Yves Zenou (2012), "Juvenile Delinquency and Conformism," *Journal of Law, Economic, and Organization* 28, 1-31.

Pettersson, Tove (2003), "Ethnicity and Violent Crime: The Ethnic Structure of Networks of Youths Suspected of Violent Offences in Stockholm," *Journal of Scandinavian Studies in Criminology and Crime Prevention* 3(2), 154-172.

Phillipe, Arnaud (2017) "Incarcerate One to Calm the Others? Spillover Effects of Incarceration Among Criminal Groups," TSE Working Paper No. 17-840.

Rendall, Michelle, Philip Ushchev and Yves Zenou (2019), "Which peers matter?", Unpublished manuscript, University of Monash.

Rigterink, Anouk S. (2019), "The Wane of Command. Evidence on Drone Strikes and Control within Terrorist Organizations," Unpublished manuscript, University of Oxford.

Sarnecki, Jerzy (1986), "Delinquent Networks," Report No. 1986:1, National Council for Crime Prevention, Stockholm, Sweden.

Sarnecki, Jerzy (1990), "Delinquent Networks in Sweden," *Journal of Quantitative Criminology* 6(1), 31-50.

Sarnecki, Jerzy (2001), *Delinquent Networks: Youth Co-offending in Stockholm*, Cambridge University Press.

Sarnecki, Jerzy and Tove Pettersson (2001) "Criminal Networks in Stockholm," In: Malcom W. Klein, Hans-Jürgen Kerner, Cheryl L. Maxson and Elmar G. M. Weitkamp (Eds.), *The Eurogang Paradox: Street Gangs and Youth Groups in the U.S. and Europe*, Boston: Kluwer Academic Publishers, pp. 257-272.

Seidler, Patrick and Rick Adderly (2013), "Criminal Network Analysis Inside Law Enforcement Agencies: A Data-Mining System Approach under the National Intelligence Model," *International Journal of Political Science & Management* 15(4), 323-337.

Sierra-Arevalo, Michael and Andrew V. Papachristos (2015), "Applying Group Audits to Problem-Oriented Policing," in Gisela Bichler and Aili E. Malm (Editors) *Disrupting Criminal Networks: Network Analysis in Crime Prevention*, Boulder: First Forum Press, Lynne Rienner Publishers, Inc., 27-46.

Stevenson, M. (2017), "Breaking Bad: Mechanisms of Social Influence and the Path to Criminality in Juvenile Jails," *Review of Economics and Statistics* 99, 824-838.

Sutherland, Edwin H. (1947), *Principles of Criminology*, Fourth edition, Chicago: J.B. Lippincott.

Tayebi, Mohammad A. and Uwe Glässer (2011), "Organized Crime Structures in Co-Offending Networks," *IEEE Ninth International Conference on Autonomic and Secure Computing (DASC)*, pp. 846-853.

Tintelnot, Felix, Ayumu Ken Kikkawa, Magne Mogstad, and Emmanuel Dhyne (2018), "Trade and Domestic Production Networks," NBER Working Paper 25120.

Ushchev, Philip and Yves Zenou (2018), "Social Norms in Networks," CEPR Discussion Paper No. 13250.

Warr, Mark (2002) *Companions in Crime: The Social Aspects of Criminal Conduct*, Cambridge: Cambridge University Press.

Xu, J.J. and H. Chen (2005), "CrimeNet Explorer: A Framework for Criminal Network Knowledge Discovery," *ACM Transactions on Information Systems* 23, 201-226.

Zenou, Yves (2016), “Key Players,” In: Y. Bramoullé, B.W. Rogers and A. Galeotti (Eds.), *The Oxford Handbook of the Economics of Networks*, Oxford: Oxford University Press, pp. 244-274.

Zhang, Sheldon (2014) “Snakeheads and the Cartwheel Network: Functional Fluidity as Opposed to Structural Flexibility,” in Carlo Morselli (Editor) *Crime and Networks*, New York: Routledge, Taylor & Francis, 13-27.

Zhang, Sheldon and Ko-Lin Chin (2002) “Enter the Dragon: Inside Chinese Human Smuggling Organizations,” *Criminology* 40(4), 737-768.

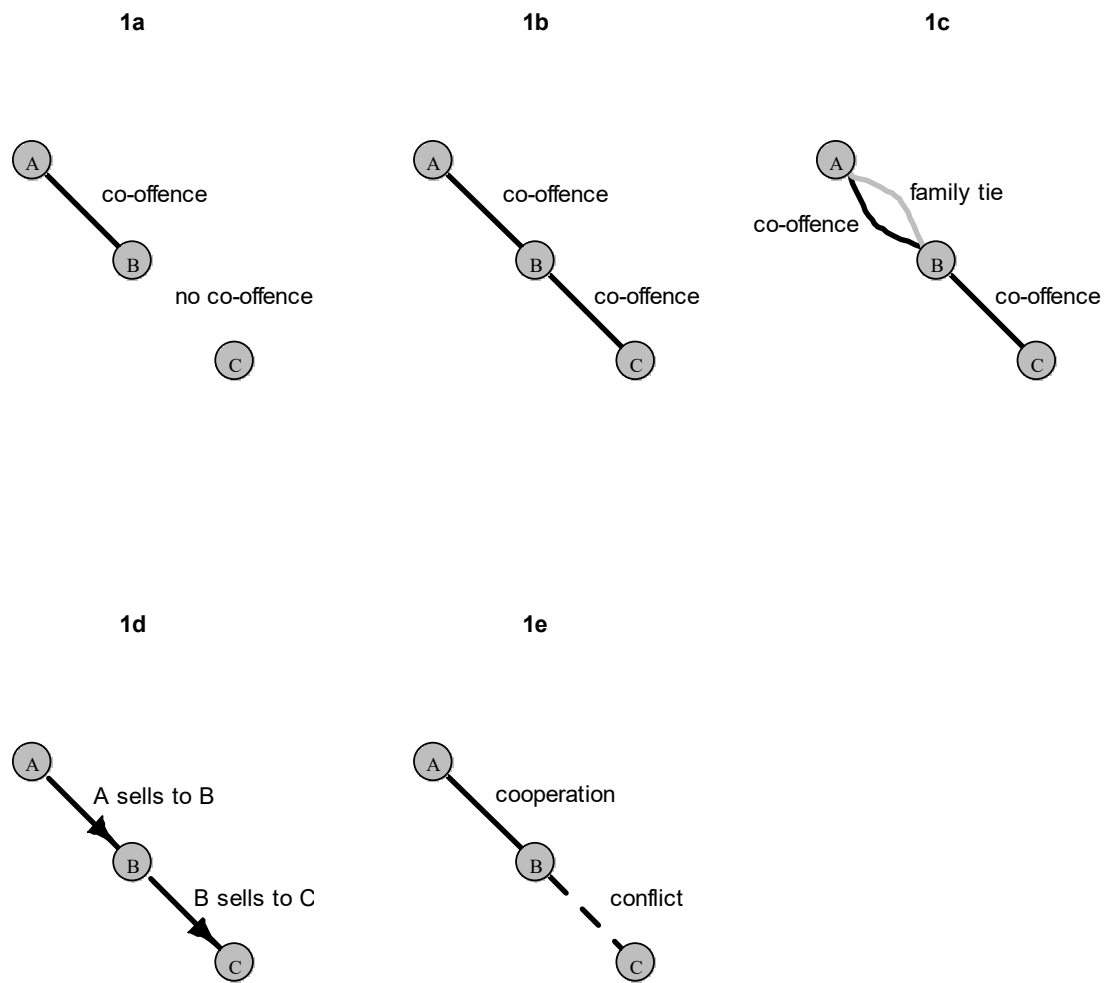
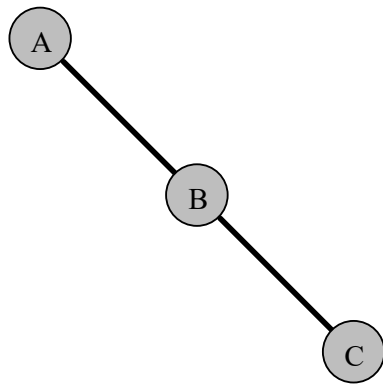


Figure 1. Different types of links between agents in a network.

2a



2b

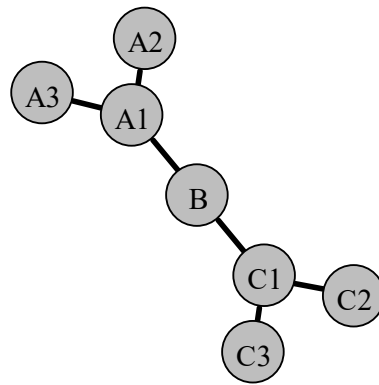
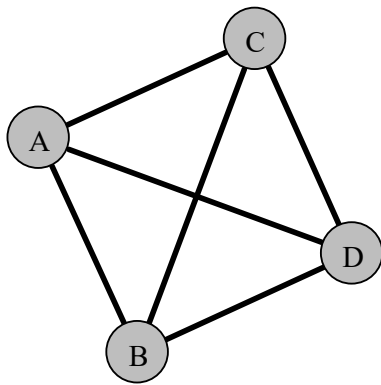


Figure 2. Agent B has the highest betweenness centrality. Agents A1 and C1 have the highest degree centralities.

3a



3b

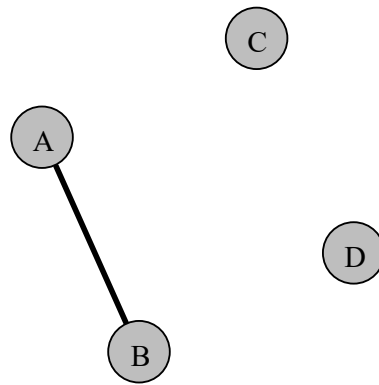


Figure 3. Panel 3a depicts a dense network. Panel 3a also depicts a clique. Panel 3b depicts a sparse network. Agents A and B in Panel 3b form a clique.