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Understanding optimal criminal networks

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We develop a theory of optimal networks in the context of criminal organizations. In this framework the criminals choose their network links with others according to a set of specified costs and benefits to participation. The optimal number and configuration of links within each network is solved for a set of 10,000 parameter simulations specifying the direct cost of links between agents, the benefit to connections, and the cost of being in the network with others. In addition, agents determine the size of the optimal network. This framework allows consideration of a variety of crime policy scenarios. In particular, removing the 'key player', the best strategy when the network is exogenous, may not be the optimal strategy in an environment in which the agents can change the size and structure of the network endogenously. More generally, optimal crime policy may be different if the criminals are aware of the policing strategy and can alter their network.

Keywords: organized crime; criminal networks

Introduction

For 70 years social scientists have discussed crime in the context of social networks. Hard on the heels of one of the early mathematical and empirical studies of what we now call a 'social network' by Moreno in 1934, Sutherland used the idea of a network to describe the relationships that existed and guided loose 'organizations' of thieves in their criminal endeavours.[1]

By a social network we mean a group of individuals together with the set of links that connect them. These links can represent a wide variety of social or other connections: communication channels, friendships, family relationships, criminal or business relationships, etc. The connections can be bidirectional or unidirectional and can reflect a measure of the intensity of the relationship or simply its presence.

Our purpose in this paper is to discuss and apply an economics approach to the theory of networking in the study of crime. For this purpose networks may be thought of as coming in two important varieties: (i) those that describe a set of fixed, pre-existing relationships like kinship ties; and (ii) those that arise from some behavioural process whereby the agents choose both the number of individuals participating in the network and the configuration of links. The vast bulk of analysis in social science is confined to the first variety. Consequently, the configuration of the networks, be it friendship groups or criminal organizations, is taken to be outside the scope of analysis. Most scholars are instead interested in characterizing the *observed* network for various purposes. Measures related to the number and configuration

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1. J. Moreno, *Who Shall Survive?: A New Approach to the Problem of Human Interrelations* (Nervous and Mental Disease Publishing Co.: Washington, DC, 1934); E. Sutherland, *The Professional Thief: by a Professional Thief. Annotated and Interpreted by Edwin H. Sutherland* (Chicago, IL: University of Chicago Press, 1937).

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of extant nodes and links such as 'centrality', 'betweenness', 'density' and other formalizations[2] are computed to help understand any number of relevant issues. In the context of crime, policy is frequently linked to identifying or removing an actor who is important in some dimension or in destabilizing a particular network.

Our approach generalizes the case in which the network structure is taken as fixed exogenously to an analysis in which the configuration of the network itself is an object of choice. We are thus interested in networks that have a *raison d'être*, as a consequence of purposeful behavioural choices made by the network members. This would seem to be particularly appropriate in the context of criminal networks. First, while there are examples of criminal activity based on kinship or regional relationships, even in these cases not every member of a family nor every person in a community is involved in the criminal activity. Writ broadly, the idea of a network as a pre-existing set of relationships in many cases begs the fundamental question as to why a particular network structure has been formed instead of any of a large number of alternative networks.

Second, once we recognize that the criminal network structure itself is an object of choice by the participants, it forces a very different perspective on the appropriateness and usage of standard measures such as connectivity and centrality. If as a prescription for crime reduction, for example, a policy based on a fixed network calls for removing the 'central' or 'key player' in the network, we want to be sure that it is the right 'key player' who is targeted if the network structure in fact is flexible. While irrelevant if the network is fixed, should criminals be aware of a particular law enforcement policy threat, they may choose to alter (ex-ante or ex-post) their network to one less vulnerable to that policy. Facing different specific threats, it would be surprising to see the same network always be formed if criminals have the ability to modify the network, even if this ability is subject to constraints.[3] Consequently, we argue that the crime combating policy strategists must recognize that criminals have the ability to alter the structure of the network itself. As a result, as we demonstrate in this paper, in general the best policies are not the same as those designed for fixed networks.

To be able to analyse the criminals' purposeful choice of network structures as well as their optimal response to various law enforcement policies and strategies, we develop a formal model of criminal networks. This model, after calibration with data on actual networks and the costs and benefits of particular criminal or terrorism activities, can be used as forecasting tool in designing crime combating policy.

The social networks approach to the study of criminal organizations

Networks in Criminology

Criminologists have used networks to frame any number of important issues such as delinquency, violence, the consequences of drug abuse among women, police socialization,

2. For an excellent review see S. Wasserman and K. Faust, *Social Network Analysis: Methods and Applications* (Cambridge: Cambridge University Press, 1994).

3. Economists typically distinguish short-run from long-run responses on the basis of various constraints on possible choices characterizing the short-run. Analogously, we might imagine an observed network as a short-run outcome of a process in which the players are unable for some time to change the size or the number of links in the network. Further, this is not to say that networks are not influenced by exogenous relationships like family or social ties. What is important is that the actual choice of the size and structure of the network, possibly subject to those constraints (which are not absolute) has not been modelled.

co-offending, criminal intelligence gathering and criminal displacement to name but a few.[4] Quintessentially, social network theory has been used as a way to understand organized crime ranging from mafia families to street-level drug dealing. For instance, Bruinsma and Bernasco[5] suggest that 'the traditional view of criminal groups as centrally controlled organizations has been replaced by the notion of criminal networks' while Kenney provides extensive list of references and a guide to the use of social networks for analysing crime.[6]

Economic sociologist Ronald Burt, one of the 'fathers' of network theory, introduced the idea that gaps between two different groups connected through a single key agent ('broker') can be thought of as 'structural holes' in social networks. Burt studied supply chain managers and hypothesized that people who span such structural holes are those who 'live at the intersection of social worlds', and are 'at higher risk of having good ideas' as they are exposed to more diversity, while people who are part of more cohesive social networks (e.g. colleagues in the same office) tend to think and act the same. Burt's theory implies that among networks with a given number of non-redundant links, those who span more diverse sets of players (sub-networks) provide more information. Burt's theory has been widely used in sociology and criminology and brings important insights as to the benefits and costs of different network structures that we use in our analysis.[7]

There are several important aspects of organized crime that have been successfully analysed using network theory, although some authors have reservations. The works of McIllwain and McGloin[8] aptly illustrate these differences of opinion. McIllwain explicitly treats organized crime from a social networking perspective, in contrast to what he argues has been its major characterizations from institutional or organizational perspectives: as a set of patron–client relationships, or as part of the 'business of organized crime'. His take on the mafia is reminiscent of Burt's[9] as he finds that, 'they serve as brokers of information and services between various subgroups' and consequently, the network they inhabit is fundamental and serves as an underpinning to all of the earlier approaches. McGloin, on the other hand, while arguing that network analysis is useful for the study of gangs in the broad sense, maintains that it is not necessarily useful for characterizing all gangs.

4. J. Sarnecki, *Delinquent Networks: Youth Co-offending in Stockholm* (Cambridge: Cambridge University Press, 2001); C. Schreck, B. Fisher, J. Miller and J. Mitchell, 'The Social Context of Violent Victimization: A Study of the Delinquent Peer Effect', *Justice Quarterly* 21 (2004): 23–47; S. James, J. Johnson and C. Raghavan, 'I Couldn't go Anywhere: Contextualizing Violence and Drug Abuse: A Social Network Study', *Violence Against Women* 10 (2004): 991–1014; M. Sato, 'Police Recruits' Training and the Socialization Process: From the Network Perspective', *Police Journal* 76 (2003): 289–303; L. Hoffer, *Junkie Business: The Evolution and Operation of a Heroin Dealing Network* (Ann Arbor, MI: UMI Press, 2002); M. Sparrow, 'The Application of Network Analysis to Criminal Intelligence: an Assessment of the Prospects', *Social Networks* 13 (1991): 251–74; S. Deutsch, J. Jarvis and G. Parker, 'A Network Flow Model for Forecasting and Evaluating Criminal Displacement', *Evaluation Quarterly* 3 (1979): 219–35.

5. G. Bruinsma and W. Bernasco, 'Criminal Groups and Transnational Illegal Markets: A More Detailed Examination on the Basis of Social Network Theory', *Crime, Law and Social Change: An Interdisciplinary Journal* 41 (2004): 79–94.

6. M. Kenney, 'The Architecture of Drug Trafficking: Network Forms of Organisation in the Colombian Cocaine Trade', *Global Crime* 8 (2007): 233–59.

7. R. Burt, *Structural Holes: The Social Structure of Competition* (Cambridge, MA: Harvard University Press, 1992).

8. J. McIllwain, 'Organized Crime: A Social Network Approach', *Crime, Law and Social Change* 32 (1999): 301–23; J. McGloin, 'Policy and Intervention Considerations of a Network Analysis of Street Gangs', *Criminology and Public Policy* 4 (2005): 607–36.

9. R. Burt, *Structural Holes*, 311.

In particular, she has reservations about the relevance of the 'key player' approach for analysis and intervention. If the gangs in question can easily re-form or are sufficiently loosely associated, then they are far less structured than a simple relationship mapping suggests.

Morselli and Tremblay[10] use a network approach to examine the gains from criminal earnings. By emphasizing the theory of 'non-redundant' networking derived from Burt's theory of structural holes, they find that 'brokerage-like' networking raises offenders' market earnings. However, networking does not affect non-market incomes or 'predatory' offenders' incomes. When engaged in illegal market-oriented offences, criminals who stand between different networks that have no additional contacts with each other are the participants who generate income higher than that of the other members of the network. We find similar results in our theoretical model.

In yet another application, Albanese argues for a generic network approach by function, rather than looking at particular individuals, in his application of the network approach to human trafficking.[11] He suggests that tasks of recruiting, transporting and exploiting, while variable among individuals, reflect fundamental characteristics of a network of required activities to permit the 'white slave' trade to persist. He contrasts networks with 'traditional crime groups', arguing that the associations made up of networks are less persistent and less well-organized.

The role of networks is distinct and stands in contrast to approaches that emphasize simple association. For example, Haynie[12] argues that network 'density' (the frequency of links among players) plays an important part in delinquency behaviour – peer association with higher network density is associated with greater delinquency. Consequently, the structure of the network, as well as simple peer effects (which are usually thought of as averages of associates' attitudes), is germane to observed criminal behaviour. Location in the network, which can be quantified through measures of density, centrality and popularity, provides a better predictor of delinquent involvement than simply knowing the attitudes of peers. Haynie also finds that an adaptation of Sutherland's theory of differential association and Akers' emphasis on peer behaviour is consistent with evidence found by knowing the intensity of association as a function of the location in the network.[13]

Natarajan emphasizes the network structures associated with different phases of criminal activities.[14] She uses telephone intercepts to explore network density, cut-points and centrality in the context of heroin dealing. She finds that while the 'star' topology reflects best the dealer and his distributors, and that dealers alone are connected to suppliers, the suppliers themselves are also connected to each other. Most of the players

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10. C. Morselli and P. Tremblay, 'Criminal Achievement, Offender Networks and the Benefits of Low Self-Control', *Criminology* 42 (2004): 773–804.
11. J. Albanese, 'Criminal Network Approach to Understanding & Measuring Trafficking in Human Beings', in *Measuring Human Trafficking* (New York: Springer 2004).
12. D. Haynie, 'Delinquent Peers Revisited: Does Network Structure Matter?', *American Journal of Sociology* 106 (2001): 1013–57; D. Haynie, 'Neighborhood Characteristics, Peer Networks, and Adolescent Violence' *Journal of Quantitative Criminology* 22 (2006): 147–69.
13. E. Sutherland, *Principles of Criminology*, 4th edn (Philadelphia, PA: J. B. Lippincott, 1947); R. Akers, *Deviant Behavior: A Social Learning Approach*, 3rd edn (Belmont, CA: Wadsworth, 1985).
14. M. Natarajan, 'Understanding the Structure of a Large Heroin Distribution Network: A Quantitative Analysis of Qualitative Data', *Journal of Quantitative Criminology* 22 (2006): 171–92.

in the network have a single contact (208 out of 294 participants), and only about 38 of 294 players were active in the sense of having multiple phone calls to each other. The nature of the organization itself is not well defined by traditional forms of top-down hierarchical structure, and Natarajan speculates on the possibility that there may be little organization other than that imposed by prosecutors. Without an ‘organization’ it is particularly difficult for law enforcement to make a case.

While it may be difficult to prosecute organizations that are characterized by a network rather than by a more formal structure, more instrumentally, Dombroski et al.[15] propose using network theory to identify such covert organizations. By using theories about triad closure and adjacency, they are able to show that, under some circumstances, it is possible to identify elements in the network that are unobserved.

In a paper close to what we are analysing here, Carley et al.[16] ask the question: what is important for destabilizing networks? They input various measures of network flows, centrality, cut-points and the like, into a computer program (ThreatFinder) that assesses the risk to the intrinsic structure of an organization. Although their interest is primarily in large-scale networks, there are many policy experiments that they explore to examine the features that lead to group stability. They find that centrality measures point to those actors who should be removed to destabilize the network in the most efficient way.

Tsvetovat and Carley[17] carry the analysis somewhat further by examining what leads covert networks that have been attacked to re-juvenate. They consider the effect of policies that have focused on centrality, betweenness and the like to harm the network by partitioning the cells. Although directed toward networks in which the participants display some degree of isolation, simulations suggest that the existence of latent resources in the network is key to their recovery. Those networks in which it is possible to bypass the ‘gatekeeper’ and contact a member of a disrupted cell recover relatively quickly while those that have no additional contact points other than the gatekeeper (who has been removed in the experiment) remain disrupted.

The economics approach to social networks

Much of the early work analysing the trade-offs between the costs and benefits of creating and maintaining links within a network originated in economic sociology. In a seminal contribution, the economic sociologist Mark Granovetter introduced the distinction of ‘strong’ vs ‘weak’ ties in a job search context, observing that people who obtained jobs through social contacts often did so through ‘strong’ ties, i.e. through people they knew well and with whom they had considerable interaction, but, even more often, they obtained jobs through contacts with whom they had ‘weak’ ties: people with whom they had looser interactions.[18]

15. M. Dombroski, P. Fischbeck and K. Carley, ‘Estimating the Shape of Covert Networks’, *Proceedings of the International Command and Control Research and Technology Symposium*, Washington, DC (2003).
16. K. Carley, J.-S. Lee and D. Krackhardt, ‘Destabilizing Networks’, *Connections* 24 (2002): 79–92.
17. M. Tsvetovat and K. Carley, ‘Bouncing Back: Recovery Mechanisms of Covert Networks’, *NAACSOS Conference*, 2003, Day 3, http://www.casos.cs.cmu.edu/events/conferences/2003/proceedings.html.
18. M. Granovetter, ‘The Strength of Weak Ties’, *American Journal of Sociology* 78 (1973): 1360–80.

For the last 15 years research using networks in economics proper has gradually been building. Jackson summarizes many of the theoretical developments.[19] The economist's paradigm is somewhat different from the criminologist's described in the previous section. Economists typically start with the assumption that the observed network is a result of forces that lead to an 'optimal' outcome. The economic approach therefore models networks as the result of strategic and intentional interaction among agents. The main postulate is that members of the network receive payoffs that are dependent on the network structure.

Sharing this common assumption, one strand of research takes the network structure as given and analyses or compares outcomes achieved in a strategic equilibrium for different network structures.[20] Another, more recent, approach that we build upon attempts to model network formation itself as the result of a (strategic) optimization process. Links are formed at the discretion of the individuals involved and game theory is used to predict what types of 'stable' networks emerge.[21]

The literature associated with network stability is primarily interested in whether 'socially optimal' networks are stable, and if not, what mechanisms may ensure stability. In one stylized example that shares common elements with our model, Jackson and Wolinsky model a communication network in which being connected to another player carries benefits that deteriorate with distance. Like in our findings below, they show that, for different configurations of cost and benefit parameters, different stable networks emerge – the 'full' network, the 'star' network or the 'empty' network.[22] Further contributions extend these ideas in various directions, e.g. in Brueckner, who endogenizes the probability and cost of links, Calvo-Armengol, who studies probabilistic job information networks, and Calvo-Armengol and Zenou, who examine job matching.[23]

In applied work, most authors take the networks as extant and report implications for agents' behaviours. For example, Munshi finds that social networks play a significant role

19. M. Jackson, 'The Economics of Social Networks', chapter 1 in *Advances in Economics and Econometrics, Theory and Applications*, ed. R. Blundell, W. Newey and T. Persson (Cambridge: Cambridge University Press, 2006); M. Jackson, 'The Study of Social Networks in Economics', in *The Missing Links: Formation and Decay of Economic Networks*, ed. J. Rauch (New York: Russell Sage Foundation, 2007); M. Jackson, 'Network Formation', in *The New Palgrave Dictionary of Economics and the Law* (Macmillan Press, 2008).

20. Examples of this approach are: C. Ballester, A. Calvo-Armengol and Y. Zenou, 'Who's Who in Networks: Wanted the Key Player', *Econometrica*, 74 (2006): 1403–17; Y. Bramoulle and R. Kranton, 'A Network Model of Public Goods: Experimentation and Social Learning', mimeo (University of Toulouse, 2005); and A. Calvo-Armengol and M. Jackson, 'The Effects of Social Networks on Employment and Inequality', *American Economic Review*, 94 (2004): 426–54.

21. M. Jackson, 'The Stability and Efficiency of Economic and Social Networks', in *Advances in Economic Design*, ed. S. Koray and M. Sertel (Springer: Heidelberg 2003); M. Jackson, 'A Survey of Models of Network Formation: Stability and Efficiency', in *Group Formation in Economics: Networks, Clubs and Coalitions*, ed. G. Demange and M. Wooders (Cambridge: Cambridge University Press, 2004) are two excellent reviews.

22. M. Jackson and A. Wolinsky, 'A Strategic Model of Social and Economic Networks', *Journal of Economic Theory*, 71(1996): 44–74; V. Bala and S. Goyal, 'A Non-cooperative Model of Network Formation', *Econometrica* 68 (2002): 1181–230 extend this analysis to directed networks with similar conclusions.

23. J. Brueckner, 'Friendship Networks', mimeo (University of Illinois, 2003); A. Calvo-Armengol, 'Job Contact Networks', *Journal of Economic Theory*, 115 (2004), 191–206; A. Calvo-Armengol and Y. Zenou, 'Job Matching, Social Network and Word-of-Mouth Communication', CEPR Discussion Paper 2797 (2001).

in job information transmission among Mexican immigrants to the United States. Further, smaller and 'younger' networks reduce the chance of finding a job.[24] Calvo-Armengol and Jackson model the process of job information transmission, allowing for varying intensity in social contacts (à la Granovetter) and directed links. These findings emphasize the recognition that policy interventions such as unemployment insurance need to reflect the structure of the network in which people find themselves.[25]

Criminal networks and our approach

One significant contribution economics has made to network theory is the focus on 'why' we observe the networks with specific features that have been reported by criminologists, sociologists and others. A fundamental requirement for understanding why certain types of networks form and others do not is to have a model of how the network structure affects individual behaviour. Our approach to characterizing crime networks lies in between the approaches of 'characterizing behaviour in a given network' and 'identifying which networks would arise optimally' discussed above. We first model the costs and benefits of being in a criminal network and derive the equilibrium crime level that arises in any particular network structure. We then find which network structures arise as consequence of maximizing a meaningful criterion, which in our case is 'total profits' (benefits minus costs) received by the criminal organization.

We define the concept of an *optimal network* as the profit maximizing network structure that will be attained as a result of competition among criminal groups. The idea is that free entry (or the threat) of new, competitor networks ensures that only profit maximizing structures survive. Equivalently, the same outcome can arise from the operation of a criminal 'boss' who optimizes over possible network structures and selects the organizational structure that generates highest profits.[26]

In a pioneering example of the economics approach of characterizing criminal networks, Ballester, Calvo-Armengol and Zenou (hereafter BCZ) model the incentives of individuals to engage in crime as explicitly dependent on the structure of links among them.[27] Each criminal chooses a level of 'effort' (criminal activity) for the given network structure[28] and given the effort levels of all other members in the network. The chosen effort level determines the criminal's net payoff, defined as the benefits from doing crime

24. K. Munshi, 'The Identification of Network Effects: Mexican Migrants in the U.S. LaborMarket' (Working Paper, University of Pennsylvania, 2002).
25. A. Calvo-Armengol and M. Jackson, 'Networks in Labor Markets: Wage and Employment Dynamics and Inequality', *Journal of Economic Theory* 132 (2007): 27–46; A. Calvo-Armengol and M. Jackson 'The Effects of Social Networks on Employment and Inequality', *American Economic Review* 94 (2004): 426–54; See also Y. Ioannides and L. Loury, 'Job Information Networks, Neighborhood Effects, and Inequality', *Journal of Economic Literature* 42 (2004): 1056–93 for an extensive review on networks in labour economics, with applications to job information dissemination, neighbourhood effects and inequality.
26. Profits here should not be interpreted literally as monetary rewards and can include other goals (e.g. maximal damage, recognition, etc., which are perhaps more relevant for terrorist groups).
27. C. Ballester, A. Calvo-Armengol and Y. Zenou 'Who's Who in Crime Networks. Wanted: the Key Player' (Working Paper, 2004). See also A. Calvo-Armengol and Y. Zenou, 'Social Networks and Crime Decisions: The Role of Social Structure in Facilitating Delinquent Behavior', *International Economic Review* 45 (2004): 939–58 who use a similar model to analyse entry into crime.
28. Unlike in our model, in BCZ the configuration of links and nodes is fixed and not allowed to change.

less the costs – which are not explicitly modelled but might include being captured and penalized if caught, the psychic costs of being a criminal, out-of-pocket costs, etc. The configuration of the individual criminal efforts and the aggregate crime level are determined in Nash equilibrium[29] and, importantly, depend on the assumed network structure. BCZ find that individuals with higher ‘Bonacich centrality’,[30] i.e. those who have the highest number of direct and (appropriately weighted) indirect links with all others, exert the most crime. They also define ‘key players’ in the network as those who are the most influential in terms of the overall crime level. This means that removing such a key player from the network will cause the maximum drop in crime, compared with removing any other player. An obvious policy implication is that crime fighting policy that directly targets such individuals, holding the network fixed, will be more successful than a policy targeting random individuals or targeting those who do the most crime.

While our theoretical model borrows liberally from the analysis of BCZ and retains some of their notation and the basic spirit of their theoretical model, we modify and extend BCZ’s contribution in several significant ways. First, we adopt a different cost–benefit configuration for the players that we think better reflects the operation of actual criminal organizations. Namely, we assume that the benefits for an individual doing crime in the network depend positively on the connections the criminal has with others and on their crime efforts, while the costs of doing crime depend on aggregate criminal activity. The interpretation is that better connected criminals and/or criminals whose ‘partners’ are more active should have higher productivity and obtain higher payoffs. On the other hand, higher aggregate crime is likely to draw more attention by law enforcement and increase everyone’s costs.

Second, while we characterize the Nash equilibrium in crime levels within a given network, we do not stop there. Instead, our primary objective is to look for the ‘optimal network’ not only for a given number of agents, but also over various network sizes – a variable number of agents. We define the ‘optimal network’ as the network that maximizes aggregate profits from doing crime for the criminals involved. This does not have to coincide (and in fact does not coincide, as we describe below) with the network maximizing aggregate criminal activity. That is, on top of the within-network optimization with everyone choosing their crime level, we add a second important layer of optimization: searching for the optimal network structure that will arise. The network structure includes both the pattern of links among agents and the number of agents themselves.

Third, not unlike BCZ’s original motivation, we are also interested in the effect of crime fighting policies for observed crime levels. However, with the addition of the extra layer of optimization that now includes the network structure, this question is not as straightforward as finding BCZ’s ‘key player’. Specifically, when analysing crime fighting policy, we recognize that the criminals’ knowledge of the policy will affect the structure of the network being formed. While, by definition, it is true that taking out the ‘key player’ will cause the greatest reduction of criminal activity for any given network, should criminals be aware of such a policy, our optimization suggests that they will adapt their network structure in such a way as to reduce (or minimize) the impact of the policy. As a result, we show examples, in which a ‘myopic’ crime combating policy targeting the network’s key player performs worse

29. Nash equilibrium is a solution concept of a game involving two or more players, in which each player is assumed to know the strategies of the other players. In Nash equilibrium no one has anything to gain by changing one’s strategy unilaterally given the strategies of all others.
30. P. Bonacich, ‘Power and Centrality: A Family of Measures’, *American Journal of Sociology* 92 (1987): 1170–82.

than targeting another player! We elaborate further on this 'Lucas critique'[31] argument below. To understand the framework necessary to develop these points we move first to a formal characterization of our approach and then turn to the way in which policy would be different. Rather than look exclusively at a general framework, we develop the theory in the context of a manageable and limited example.

A theoretical model of criminal networks

Basic setting

At the most abstract level, suppose that there are N agents whose interaction we model as a social network. A network is defined as a list of nodes and the links between them. We assume only bi-directional links so that if agent i is connected to agent j then the reverse is also true.

For a particular network structure, the agents decide on a level of criminal activity to undertake, which we term their criminal 'effort', and which can be either zero or positive. The efforts chosen maximize the agent's 'utility' or net income: their benefits less their costs. While choosing their effort, each agent takes the structure of the network and the efforts of the other agents as given and maximizes his/her net payoff, solving the following maximization problem:

$$\max_{e_i} U_i(G, e) = y_i(G, e) - c_i(G, e) \tag{1}$$

where criminal i's income is y_i, his costs are c_i, and **e** is the vector of all agents' efforts, $e = (e_1, e_3, \ldots, e_N)$. G is the criminal network's 'adjacency matrix': a square, N-by-N matrix made up of zeros on the diagonal and zeros and ones symmetrically on the off-diagonals. The positions of the ones in G correspond to pairs of agents that are linked. That is a '1' element g_{ij} of G means agents i and j, $i, j = 1, \ldots, N$ with $i \neq j$ are linked, while $g_{ij} = 0$ would mean that agents i and j are not linked.

The next step is to flesh out the determinants of the costs and benefits of crime. To explore the consequences of networking on crime levels and payoffs, we assume: (a) that the benefits increase in the number of links a player has; (b) that through these links a player's effort interacts with other players' efforts and this interaction raises the level of income above that obtained simply by one player on his or her own; and (c) that the total amount of crime created by others in the network generates a congestion effect, increasing each agent's costs, arising (say) from a greater likelihood of being detected.

Specifically, individual i's income, y_i is given by:

$$y_i(G, e) = e_i \left(1 + \gamma \sum_{j=1}^{N} g_{ij} e_j \right) \tag{2}$$

31. The 'Lucas critique' is named after Nobel Prize winning economist Robert E. Lucas Jr, who argued that, if we want to study the effect of a certain policy, we should model the structural parameters (relating to preferences, technology and resource constraints) that govern individual behaviour. We can then predict what individuals will do when they take the policy into account, and then aggregate these individual decisions to calculate the macroeconomic effects of the policy change. Designing policy based on current or historical data alone, without accounting for the expected change in people's behaviour resulting from the proposed policy, is inherently flawed and can have unintended consequences.

while individual costs, c_i, are defined as:

$$c_i(G, e) = \pi e_i \left(1 + \lambda \sum_{j=1}^{N} e_j + \delta \sum_{j=1}^{N} g_{ij}\right) \tag{3}$$

The benefit from participation in the crime activity has two components. The first is the direct effect of the individual's own activity. The second results from the interaction of the individual's own criminal effort and the sum of the efforts of other agents with whom he/she is connected. The strength of the positive effect of connectedness on the individual i's income is captured by the parameter $\gamma > 0$. The benefits of participation in crime are a function of the efforts of other criminals in the network and the structure of the network itself. The effect of an increase in individual effort is to raise an individual's income in proportion to the connections he has with the rest of the network.

The costs from the criminal activity depend on the effort that an individual makes and its interaction with the aggregate activity level (the sum of the es). The logic is that a higher level of activity is more likely to attract unwanted 'attention' to the criminal network, either from law enforcement authorities or rival organizations, which makes it costlier to do business. This 'congestion cost' of higher levels of crime is captured by $\lambda > 0$. As more people participate at higher levels of activity, the costs to all individuals rise proportionately.

In addition, we allow for direct costs accruing from the number of links agent i has to maintain – the parameter $\delta \geq 0$. This captures the idea that a connection is not 'manna from heaven', but may be a choice or depend upon a costly process of ongoing assessment. Finally, there is the scaling parameter π that determines the stand-alone cost of effort for an unconnected single player. We assume $\pi\lambda > \gamma$ to make sure that the maximum in equation (1) exists – otherwise, if the benefits of linking with others are too high, payoffs may grow out of bound since individual efforts are complements to each other.

Note that increases in individual effort increase costs quadratically. Increases in the number of connections raise cost in proportion to the number of connections and the effort level of the individual who is maintaining those connections.[32] Also, an increase in the activity level of others implies an increase in costs to the individual that is proportional to the individual's own level of activity.

Nash equilibrium

The particular configuration of efforts that simultaneously solves all the individual maximization problems in equation (1) is determined in Nash equilibrium. The basic notion of a Nash equilibrium is the idea that, given all other players' actions, player i does not want to deviate from her/his optimal action, e_i^* to any other criminal effort level. Moreover, in Nash equilibrium this must be true for all players. That is, given what everybody else is currently choosing, nobody finds it optimal to choose a different level of effort. This is why we refer to such a situation as 'equilibrium'. The assumption here is that individual players choose their efforts simultaneously and independently in a non-cooperative manner. This is more natural in a non-hierarchical criminal organization; however, below we also consider the potential role of a 'boss' (or competition among criminal organizations) in optimizing the network structure. An alternative would be to allow individual criminal levels to be optimized in a centralized way, e.g. as in a close-knit

32. Since both parties maintain a connection, we assume that both incur a cost per unit of effort.

mafia or terrorist structure. We discuss ways to extend our approach to permit multiple hierarchy levels below.

The dependence of each agent's benefits and costs on the network structure implies that in the Nash equilibrium the criminals' effort levels will be interdependent and co-determined by the specific configuration of the network. The equilibrium crime levels depend on the structure of the network and so individual payoffs also depend on the network configuration.

With the costs and benefits given in equations (2) and (3) above, each individual chooses her/his optimal crime level. For a particular network and the choice of effort by each of the others, person *i* makes an optimal choice of effort by maximizing the difference between benefit and cost in equation (1). The optimization implies that, for each participant, the additional benefit of supplying one extra unit of effort, the marginal benefit (depending on the number of agents with whom agent *i* is connected and their effort levels), must be equalized to the marginal cost of supplying an extra unit of effort. The marginal cost depends on the congestion cost and the cost of maintaining links. We are then able to calculate the equilibrium levels of effort for all the participants.[33]

In contrast to specific results tied to particular networks, there are some general results that characterize the solutions to the optimal network problem. These theoretical results characterize the Nash equilibrium in criminal activities and payoffs and their dependence on the cost and benefit parameters. To keep things non-technical and accessible we only provide heuristic, intuitive 'proofs' here.[34] The first result tells us about the way in which effort and reward are linked in the model.

Result 1: *The maximized individual payoffs from crime are quadratic in the individual's own optimal crime effort.*

This is an interesting result in that it tells us that the payoff from crime is not linear in effort.[35] A greater effort increases the reward more than proportionally. We discuss the significance of this further in conjunction with Result 3 (see below) as it is extremely important for the interplay between aggregate profits and aggregate crime level.

Our second result characterizes the dependence of the equilibrium crime levels on the cost and benefit parameters.

Result 2: *The optimal individual and total crime levels are decreasing in the stand-alone cost, π and the cost of links, δ for any network. In addition, if the network is symmetric (regular), the optimal individual and the total crime levels are decreasing in the congestion cost, λ, and increasing in the benefit of links, γ.*

The intuition for the first part of Result 2 should be clear: higher values of π scale up the costs without affecting the benefits for all players. Thus, individual crime levels and,

33. Writing out the equilibrium conditions for all agents we obtain a linear system of N equations in N unknowns that can be solved for the optimal effort levels, e_i^*. We solve analytically an example for $N = 3$ in the Appendix. In general, however, the solution is complicated and we approach the problem numerically although even this approach faces limitations arising from the complexity of optimizing over network structures networks (see more on this below).

34. The full details can be found in Easton and Karaivanov, 'The Economic Structure of Crime Networks' (Working Paper, Simon Fraser University, 2008), hereafter EK.

35. This follows from the linear-quadratic structure of the costs and benefits of crime. Intuitively, all dependence on other criminals' efforts and the network structure is embedded in one's optimal effort, e_i*, which yields that the individual's payoff is quadratic in their own effort.

by extension, total crime, decrease when π increases. Further, higher costs of maintaining links, δ have a similar effect since, for any given configuration of links embodied in G they impose a higher burden on the criminal if he tries to extend his contacts. Interestingly, the effects of the marginal benefit parameter γ and the congestion cost λ cannot be assigned in a simple unambiguous way for any possible network. The reason is that there is a complicated interaction between individual efforts and their dependence on the configuration of links (described by the matrix G). For example, higher λ increases the direct costs per unit of other players' efforts but if, in equilibrium, the sum total of other players' efforts decreases at the same time, this may actually make it more beneficial for an individual agent to supply more effort. Similarly, if G is not regular (where regular means that all members have the same number of links), an increase in the congestion cost variable λ has asymmetric effects on different agents, through the interaction with efforts of others in generating income, y_i.

The latter complications do not arise in the case of a regular (symmetric) network in which the Nash equilibrium conditions imply that all criminals will supply the same level of effort. This fact can be used to solve for the optimal crime level using the first-order optimality conditions.[36]

Optimizing over the network structure and size

What separates our approach from that of criminologists, sociologists and most other social scientists who have used networks in the study of crime and other applications hinges on the assumption that, in choosing to maximize net income, the players implicitly start with the 'correct' network. Those who have analysed networks have explicitly chosen a particular network and then asked the question, what is the level of activity that maximizes net income? This is a reasonable assumption in situations in which the links among actors are fixed or at least in part exogenously determined. One can see family ties, social relationships or even class or caste relationships as being environments amenable to such a modelling strategy. In addition, criminal networks and offenders' positions within them can be structured by neighbourhood factors, kinship or other ties outside the criminal connections; individual factors such as gender, age, etc., and outside influences such as incarceration. We might term these 'predetermined' links.[37]

However, in a broader context actors can equally choose with whom they interact. This means that the nature of the choice facing a network participant is not simply to choose a level of effort confronted by a particular pattern of links, but rather that each participant must also choose the links that will maximize net income.

We therefore add a second layer of optimization to that of the choice of effort and study the network structure that maximizes some meaningful performance measure. That is, we search over all possible networks (of fixed or variable size) to find the 'optimal' network structure.[38] Naturally, in realistic settings the optimization can be constrained – some links

36. We show analytically (see EK) that the crime levels satisfy the properties listed in Result 2. The Appendix derives a sample case.

37. These predetermined links are relevant in some cases, but they will differ by context. We are more interested in those links chosen by the participants as described below.

38. In this paper, we study connected networks only. These are networks in which each actor is linked with at least one other actor. No criminals stand alone. In principle, our theoretical model and computation methods allow us to analyse more general structures, with both connected and unconnected criminals, but given our emphasis on networks, we rule those out in this paper.

can be fixed or the number of criminals can be fixed, at least in the short term. Our method allows us to take such constraints into account and, in fact, this makes the problem easier, since it reduces the number of network structures we need to search over.

The optimization over network structures can be thought of as the result of the process of free entry of new, competitors' networks which would ensure that only the best, profit-maximizing structure survives – in the same way as perfect competition results in zero economic profits for firms. Alternatively, the optimal network can be thought of as arising from the operation of an overarching criminal 'boss' who optimizes over all possible network structures and chooses the network generating highest aggregate profits. Which of the two interpretations is more suitable depends on the particular application.

In general, finding the optimal network is a hard mathematical problem, especially for large numbers of participants. This is discussed in more detail in the next section. However, for some particular cases we are able to derive more specific results. For instance, consider the situation in which there are no direct costs of maintaining or using links. We obtain:

Result 3: *For any given network size N, if the cost of links δ is zero, the network structure that maximizes overall equilibrium crime is the full network where all criminals are connected.*

We have proved this result formally.[39] Intuitively, if links are not costly, the gain of being connected with everyone offsets the additional marginal cost of congestion. We know from equations (2) and (3) that the agents' efforts are strategic substitutes. That is, holding other things constant, an increase in someone else's effort e_j reduces criminal i's crime effort. Moreover, this substitutability is stronger if two agents are not connected ($g_{ij} = 0$ in equation (2)). Connections between participants tend to counter substitutability in efforts. Thus, when the number of direct connections is maximized, which happens in the full network, the total crime effort level is highest.

However, finding the network that maximizes total crime is not our primary goal. Instead, the economics of the problem suggests that we are likely to observe networks that maximize total payoffs. This is a result of competition among criminal organizations. The more profitable drive out the less profitable. Consequently, the payoff of doing crime and not crime *per se* is what is relevant.

Combining Results 1 and 3 identifies a trade-off that is intrinsic to the solution of the optimal profit-maximizing network. From Result 1 we know that, for a given level of total crime in equilibrium, total profits are proportional to the sum of the squares of individual crime levels. This implies that, the more 'asymmetric' the effort structure is, the higher total profit tends to be.[40] On the other hand, we know that (if link costs are zero), it is the symmetric full network structure that maximizes total crime and asymmetric structures lead to less crime, which can reduce profits. The interplay of these two effects – the former favouring asymmetric structures, like the 'star' network, and the latter favouring the full network, will depend on the particular cost and benefit structure. We show representative examples of optimal networks in the next section.

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39. EK as per footnote 34.
40. The quadratic structure means that, if a criminal supplies a disproportionate fraction of total effort, this is likely to generate higher profits. In the extreme, one criminal has to do everything, but this is inconsistent with equilibrium. To see this tendency, imagine total effort of 12 with three participants. If each has an effort of 4, total profit is 3 times 4-squared or 48. If one participant supplied the same total effort instead, 12 times 12 is 144.

We can further extend the analysis to what we term 'full optimization' by permitting the number of agents in the network also to be a choice variable. To analyse this, we compare the maximized aggregate profits networks of different sizes. Depending on the costs and benefit parameters the optimal network may be large or small. This highlights the role that choice plays since not only the configuration of the links but number of players is now a matter of choice.

Let us summarize. Our research strategy looks at networks as outcomes of a behavioural process. Traditionally, the network has been taken as exogenous to the players in the network, and analysis has answered questions in the context of that network. We believe that a more fruitful approach treats the network itself as the outcome of an optimization process. Further, the size of the network is also a potential object of choice. However, there are pitfalls in our approach. The fundamental complexity of networks is a stumbling block to extensive application.

Computation and complexity

Because networks and individuals, as opposed to just individuals are our units of analysis, there is a fundamental complexity. Keeping track of the network structure in addition to the 'usual' prices and quantities creates substantial analytical difficulties while solving for static optima and equilibria even in standard economic problems. In addition, even if all agents in the network have exactly the same preferences and technology, their position in the network or how many and which other players to whom they are connected effectively makes them heterogeneous, adding another layer of complication. Further, the externalities among the agents embedded in a network interaction can be the cause for multiple equilibria – yet another additional known source of complexity. Computational power sufficient for the analysis of these more complex problems has become generally available only recently.

In our particular setting, it is optimizing over the network itself that makes the problem complex. One of the main contributions of this paper is that we study 'optimal networks' – networks that maximize aggregate profits among all possible networks of a given size, and then across different sizes. In principle, there are $2^{N(N-1)/2}$ networks of size N. This means that, even with a small number of players, the potential number of networks becomes very large. For example, with only seven nodes there are already 2^{21} (2,097,152) networks. Thus, if we were to compute the equilibrium for every network, the computational time required would grow faster than exponentially with network size. On the other hand, it is clear that many of the possible networks are effectively the same, requiring only the re-labelling of nodes. For example, for $N = 7$ there are only 1044 unique networks. Thus, to avoid costly duplication of time and effort we only need to compute the equilibria for the different, or as they are known in graph theory, non-isomorphic networks.[41] In EK we explain the details of the numerical algorithm we use to search for the optimal profit-maximizing network in the general case.

Examples

We use numerical methods to find the optimal network. We set our four benefit and cost parameters – connectedness (γ), congestion (λ), the cost of links (δ) and stand-alone costs

41. However, even simply generating all non-isomorphic networks of given size is a difficult problem in graph theory and computer science that has not been solved for any N. See B. McKay, 'Practical Graph Isomorphism' *Congressus Numerantium* 30 (1981): 45–87.

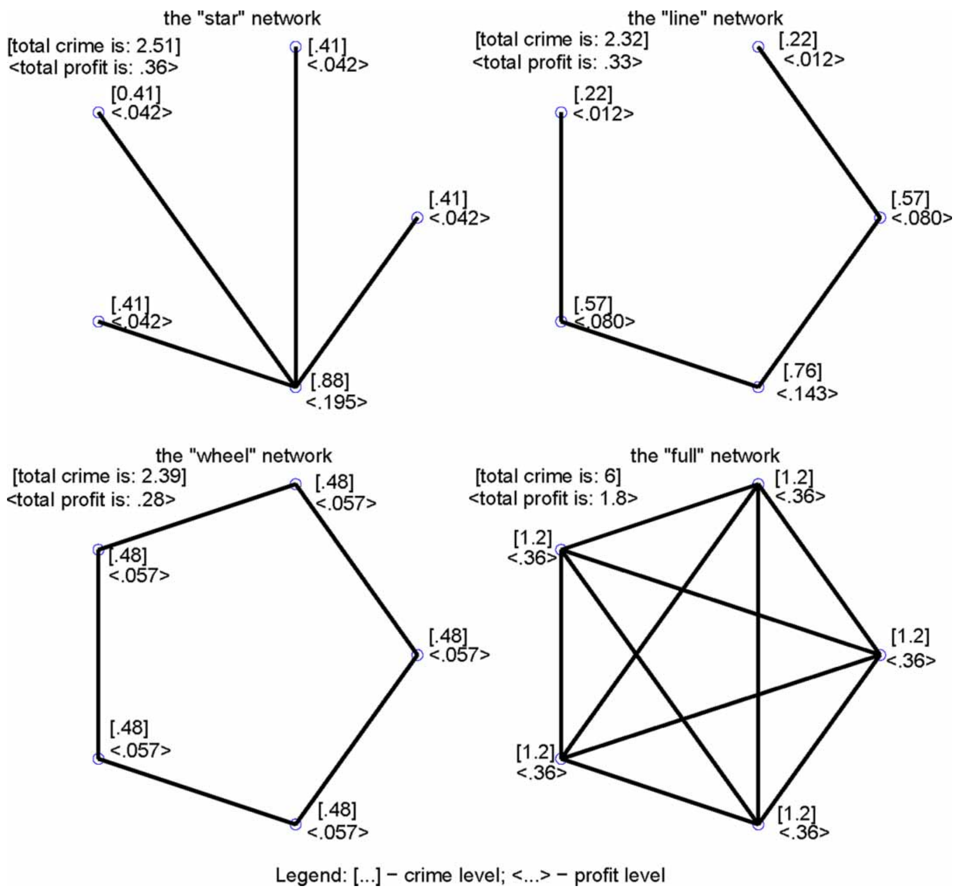

Figure 1. Nash equilibrium individual crime and profit levels (constant parameters).

of crime (π) – and calculate the levels of effort and profit for every network. The result of the optimization yields a set of profit maximizing effort (crime) levels selected over all possible networks.[42] Below we provide several representative examples[43] of optimal networks and the effects of parameters on the network structure. These examples demonstrate and further clarify the general analytical results from above.

To fix ideas, Figure 1 displays a number of different five-player networks reporting the total crime (the sum of individual efforts) and the total profit (the sum of individual profits) obtained in Nash equilibrium associated with a particular set of parameters ($\delta = 0.07$, $\gamma = 0.3$, $\lambda = 0.5$ and $\pi = 0.5$), as well as the effort and profit levels associated with each player. The configurations displayed in Figure 1 include some well-known networks: the 'star', 'line', 'wheel' and 'full' networks.

Figure 1 demonstrates that different network structures affect crime levels and profits in a significant way, both at the individual and the aggregate level. For example, for the

42. For the more technically oriented, the Appendix solves a specific example for a three-player network.
43. The chosen parameters are arbitrary but the changes in them across the examples are deliberately picked to illustrate the general trends and outcomes discussed above.

chosen parameters the ‘full’ network, in which each criminal is connected to everyone else, achieves a total crime level of 6. This is more than twice the amount of crime generated by the ‘wheel’, ‘star’ or ‘line’ configurations. Further, the figure also illustrates that there is no simple one-to-one mapping between aggregate profits and the aggregate crime level. For instance, the ‘wheel’ network produces more crime than the ‘line’ but lower overall profits. This is important because we argue that it is likely that criminals would choose (or competition will ensure the survival of) organizational forms that maximize overall net income (‘profits’) and not necessarily those that maximize the crime level. This should be kept in mind when we discuss policy implications in the next section.

Finally, Figure 1 also illustrates how an individual player’s position in the network implies a different crime (and profit) level for that individual. For example, observe the agent in the ‘star’ network connected to everyone else. His key position gives him a large share of total profits (he generates more than half of the aggregate profit), while he is only responsible for about a third of the total crime. Similarly, in the ‘line’ network the end players (those connected to a single other person only) put in the lowest effort and contribute the least to total profits, while naturally the criminal who is farthest from the end players contributes the most. The ‘wheel’ and ‘full’ structures are symmetric in terms of the connections that network members have with each other. Naturally, in equilibrium, everyone optimally creates the same amount of crime and generates the same share of income and profit.

We next illustrate the forces determining the equilibrium crime efforts (which in turn determine the choice of the optimal network structure) by exploring the inner workings of the model through varying the parameters of the environment as in Result 2 above. Holding the number of criminals in the network constant, Figure 2 displays the way that changes in the cost and benefit parameters affect the structure and total crime and profits in the optimal, profit-maximizing five-person network.

For the same parameter values as in Figure 1 ($\delta = 0.07$, $\gamma = 0.3$, $\lambda = 0.5$ and $\pi = 0.5$), the top-left panel of Figure 2 plots the optimal five-person network. The optimal structure is the ‘full’ network which achieves total profits of 1.8 and an aggregate crime level of 6. In contrast, the top-right panel depicts the optimal network structure when we keep δ, γ and π at the same level, but increase the congestion cost parameter λ to 1.5. This not only dramatically reduces realized total crime (it is now 0.55) and total profits (down to 0.05), but more importantly the ‘full’ network is no longer optimal. Instead, the optimal structure is the ‘line’. What this shows is that a different environment with higher costs of doing crime (captured by the congestion cost of being directly and indirectly associated with others) no longer leads to a network structure in which all agents are connected to each other. The reason is that now the ‘full’ network (not depicted in the new environment) generates lower total profits (by about 12%) than the ‘line’ structure.

Moving to the bottom-left panel of Figure 2, now we keep values for δ and γ as before, but let congestion costs increase to $\lambda = 0.78$ (from 0.5), and the stand-alone costs rise to $\pi = 0.64$ (from 0.5). The result is an optimal network structure resembling a ‘cell’ structure, that is a ‘full’ network (a ‘cell’) of four agents plus a fifth one connected to only one of the four. This structure is, in some sense between the line and full networks we had above. It has fewer links than the full network (because of the higher costs), but not as few as in the ‘line’ structure that arose for very high λ. Total profits and crime achieved are also in between the levels in the top-row panels of Figure 2.

Finally, the bottom-right panel of the figure depicts the optimal network structure (the ‘star’ network) that arises for $\delta = 0.07$, $\gamma = 0.3$, $\lambda = 2.3$ and $\pi = 0.5$; i.e., for even higher congestion costs, relative to the previous examples. Naturally, the result of the cost

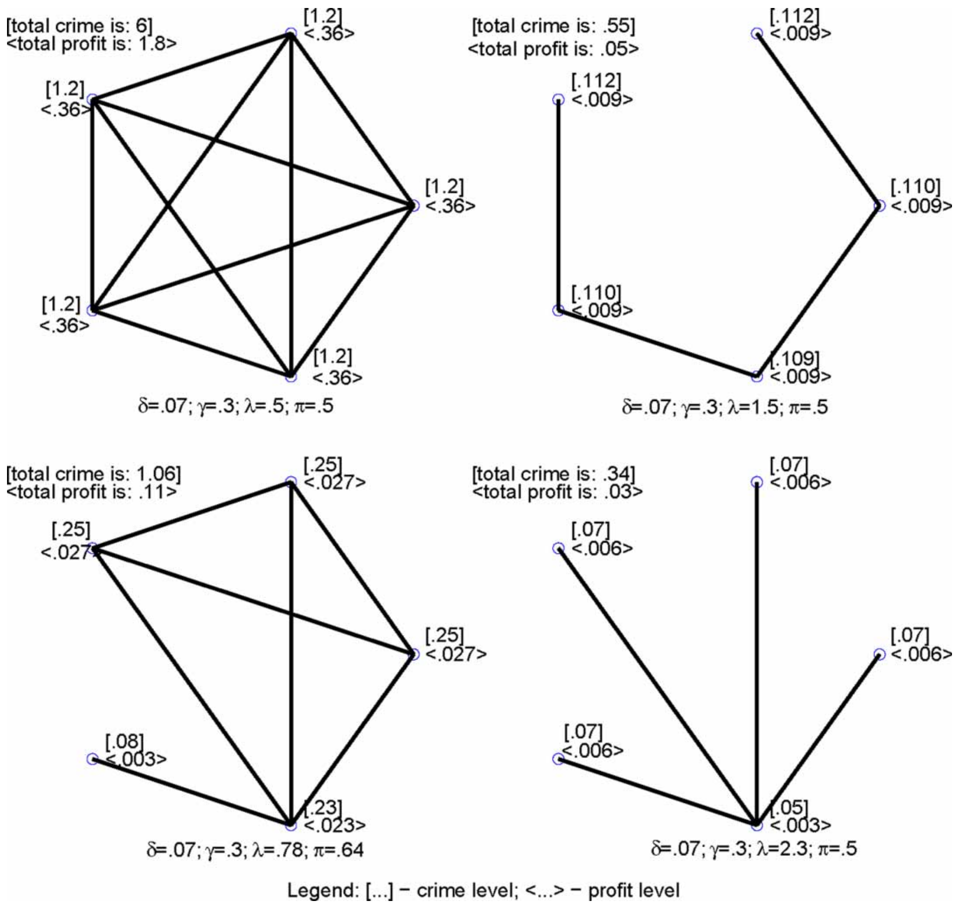

Figure 2. Optimal networks for different cost–benefit parameters.

increase is even lower total crime and profits, while more importantly, the optimal network structure shifts shape again.

The cost and benefit parameters significantly affect not only the equilibrium crime effort levels chosen but also the resulting optimal network. Higher costs are, on average, likely to lead to network structures with fewer links (recall the network size is held constant), while lower costs or (not shown in the figure) higher gains from being in the network, tend to lead to networks with more links among members.[44]

Yet what if the network size is also endogenous and can be chosen and consequently optimized to generate maximum profits? To illustrate the consequences of this requirement for full optimality, we again hold the cost and benefit parameters fixed at some representative values[45] and investigate how the optimal network structure, the total crime level, and total profits change as we vary the network size N. Figure 3 displays the optimal networks for $N = 2$ through $N = 7$.

44. EK as per footnote 34 explore those relationships in much more detail for a set of 10,000 parameter combinations.
45. For this example we use $\delta = 0.039$, $\gamma = 0.2$, $\lambda = 0.78$ and $\delta = 0.64$.

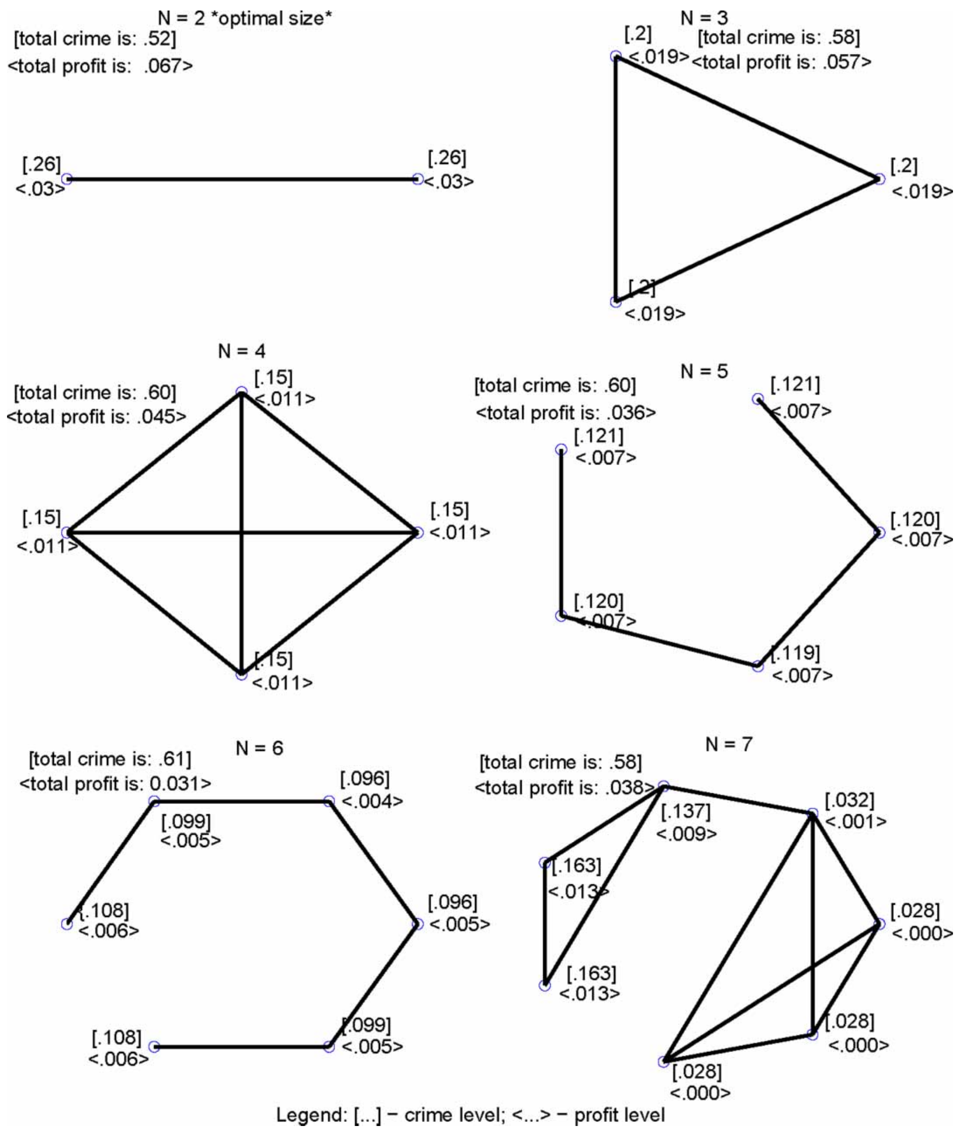

Figure 3. Optimal networks for different numbers of agents (constant parameters).

For a small number of agents (two to four), the optimal network structure is the ‘full’ network in which any two criminals are connected to each other. While the optimal structure remains the same, the group size does affect the total crime generated – it increases from 0.52 for $N = 2$ to 0.60 for $N = 4$, while the total net income for the network members in this example decreases from 0.067 to 0.045 as the size of the network rises from two to four. If the network expands further, to five or six agents, we notice a change in the optimal structure which transforms into the ‘line’ network. The total crime level still rises a little, to as much as 0.61 for $N = 6$, but total profits go down to 0.031 at the same time as the number of links necessary to maintain a connected network adds to the costs. Finally, for $N = 7$, the optimal seven-criminal structure is the ‘cell’-type network depicted on the bottom-right panel which consists of one full network of four members (on the right) and one full network of three members (on the left) connected via a single bridging link.

Over all network sizes we see that (in this parameterization) the two-agent network generates the maximum net income for the criminals (benefits minus congestion costs and costs of links), followed by the four-player and seven-player structures. That is, if one could choose over both the network structure for given network size, and also over the network size, or if competition among criminals would result in the most profitable structure, there would be two criminals operating.

Another point worth noting is that the network size that maximizes total profits does not have to coincide with the network size that would generate the highest aggregate crime level. As seen in Figure 3, total crime is maximized at $N = 6$ while such large networks are not likely to be observed if maximizing aggregate profits is the criminal organization's objective. This point has important policy implications – understanding that the criminals' objective is not maximizing total crime or harm but instead their net income should be part of designing optimal crime combating policies. We return to this issue in much more detail in the next section.

Understandably, these examples are just illustrative and in practice we would need data on actual networks and the relative size of costs and benefits involved to calibrate the exact parameter values. The point we are making here is that in our model the optimal network structure adjusts in a natural, predictable way to changes in the costs and benefits of crimes. Thus, after a proper calibration, our model has predictive power about expected changes in criminal structures arising from changes in the environment in which they operate.

Implications for crime combating policy

Within our analytical model we can study the relative effectiveness of various policies to reduce the overall crime level. That is, we can study the effects on network choice and aggregate crime from removing individual network members, increasing the probability or penalty associated to the apprehension of criminals, intercepting information flows by severing communication links or even infiltrating the criminal networks. These various crime-combating policies can be analysed quantitatively by varying the model parameters. This policy analysis can be done for any exogenously given network structure, consistent with much of the literature reviewed above, but an important next step we take here is to describe what optimal network structures would arise endogenously as a result of law enforcement using or intending to use a particular deterrence policy.

Further, our model provides testable predictions about changes in the optimal network structure arising from changes in the environment in which criminals operate. As the theoretical analysis indicates, changes in the various costs and benefits of doing crime affect both the equilibrium crime level and the types of structures chosen.

The fundamental insight is simple. When deciding on a crime-combating strategy, law enforcement or anti-terrorism authorities must take into account the criminals' likely reaction to the policy, which potentially depends upon the time frame in question. If criminals would have chosen a particular network structure without the crime fighting policy in place, there is no guarantee that the same structure would be chosen or maintained if that particular crime fighting policy is pursued. This implies that simply analyzing and classifying currently observed network structures that exist in the field, and using such historical data as a basis for deciding the policies that will make the greatest impact on the crime network, may both be flawed and have unintended consequences.

To be clear, historical data are generated by an underlying process that includes the policies of the past. Once these policies change, then one cannot expect new data to reflect old policies. Instead, we should expect them to reflect the new policies.

To deal with this profound difficulty we have developed our structural model of criminal networks exposing some of the 'deep' cost and benefit parameters of criminals' behaviour. It is capable of modelling and, subject to proper calibration, predicting the criminals' reaction to various policies used by law enforcement authorities that can be represented in a formal way within the model setting. The main point is that the predicted reaction of criminals can be explicitly accommodated in a forward-looking fashion to design the optimal crime fighting policy.

Naturally, the criminals can be constrained in various ways when reacting to possible crime combating policies. Our model allows us to study both short-term or 'constrained' responses by criminals,[46] when the network remains fixed, as well as long-term responses when the network adapts optimally (or learns) about impending or current policies. Depending on the particular network in mind, its level of sophistication, its power/hierarchical structure or degree of specialization of its members, the ability of the criminal structure to quickly adjust to policies may vary. We believe policy design should be forward looking and anticipate changes in criminal behaviour.

We clarify this general conceptual point with a specific example. Consider two possible crime-combating policies. Suppose one possible policy is to remove the 'key player' in the criminal network, as in BCZ. For the purpose of this example assume that the network players do not (or are unable to) re-optimize after the policy has been enforced (e.g. think of this as the short-term response in the terminology above).[47]

For any given network, the 'key player' policy fingers for elimination the single agent whose removal reduces total crime by the greatest amount. This is not necessarily the agent who does the most crime in the network, although it may be. The second possible policy we consider is that of removing a criminal with a probability proportional to his level of crime. This could be interpreted as removing a criminal based on his 'exposure' to the risk of being caught.

Now let us compare the effectiveness of the above two policies. For any given network structure, by definition, removing the 'key player' (as opposed to any other player) is optimal in generating the greatest reduction in crime. However, this view assumes that criminals are myopic.[48] That is, while the criminals understand that their key player is targeted, they stick with the same original network for which this key player was identified. Although information about police objectives and strategies may be secret, frequently they are highly public and part of the political process. We believe it is a reasonable conjecture to consider that (at least the most resilient and successful) criminal organizations would take the crime fighting policy (or their best prediction thereof) into account and as a result may choose a different, policy-specific, 'robust' network structure, with a different key player whose removal may not be as effective in reducing crime.

Next we provide a concrete example of the idea described above in the context of our criminal network model. This example is purposely extreme in the sense that we assume that the criminals know perfectly the direction of the policy change. Nevertheless, as long

46. For example, initially a secret change of policy direction or targeting a particular network may 'surprise' the criminal organization.
47. The case allowing for re-optimization is developed more fully in EK as per footnote 34.
48. Alternatively, it may be that the costs of information are too high.

as the criminal groups are not completely surprised, and the network structure adapts to policy to some degree, then the thrust of our example goes through.

Specifically, suppose the cost–benefit parameters are $\delta = 0.054$, $\gamma = 1$, $\lambda = 3$ and $\pi = 0.547$ and there are $N = 6$ agents in the original network. For these parameters, assuming that initially there is no crime-combating policy in place, the optimal network which maximizes aggregate profits for the criminal organization is depicted on the top panel (labelled 'no policy') of Figure 4. It is a 'cell' network consisting of four inter-connected criminals connected with two others through a bridging agent. The total

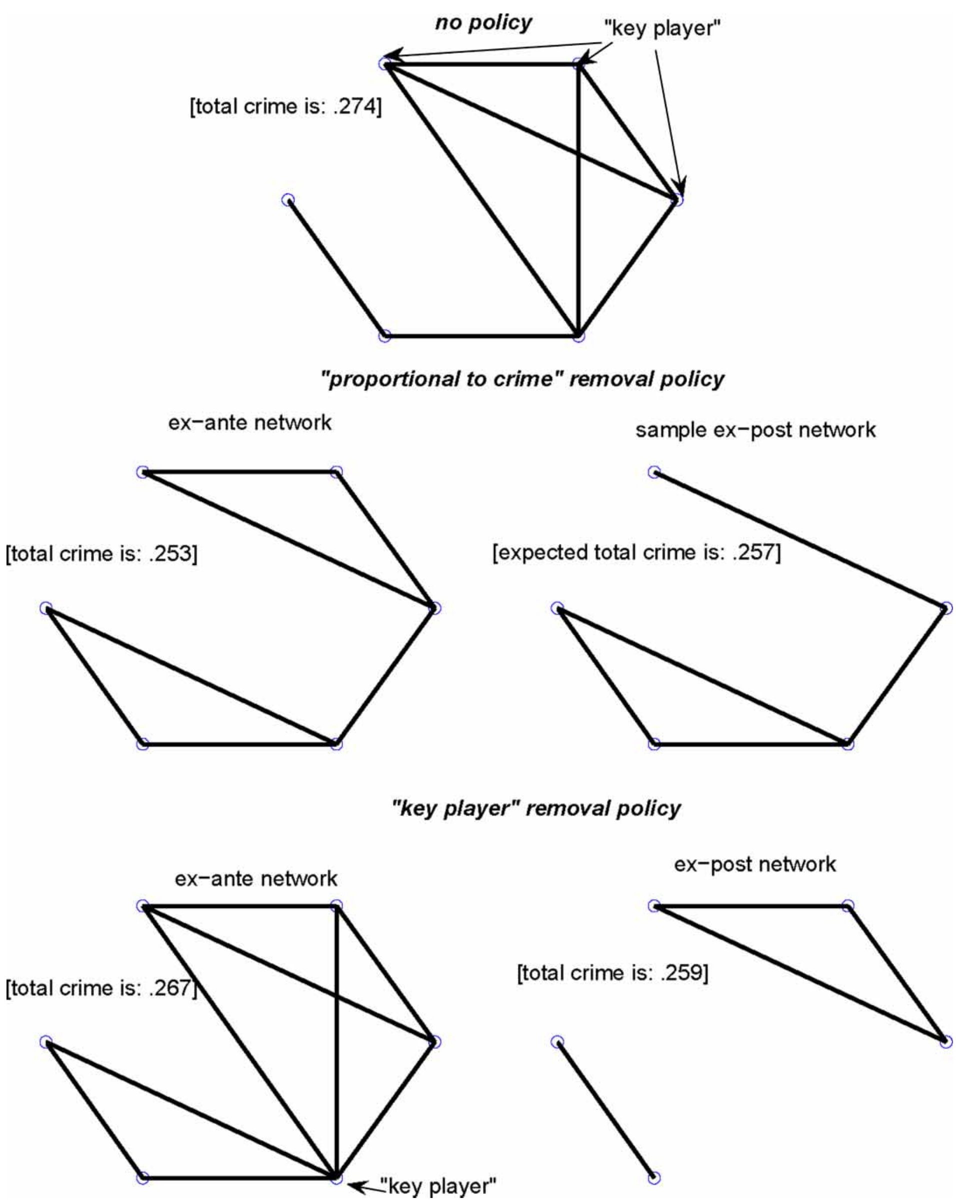

Figure 4. The effect of different crime combating policies on optimal network choice.

crime in this benchmark network is 0.274. Now consider the effect of the two possible crime reduction policies discussed above.

Suppose first that the police decide to pursue the policy of catching and removing players with a probability proportional to their crime level. Assume also, for simplicity, that this policy is effective with probability 1. That is, one criminal will always be removed and it is the 'right' criminal who is caught. If the criminals are aware (or, at some point become aware) of this policy, the optimal structure they will choose is no longer the network displayed in the top panel of Figure 4. Instead, the network structure in the middle-left panel (which we call the 'ex-ante network') will be chosen, consisting of two full three-agent networks connected with a single connection between them. Once a player is removed, the middle-right network (the 'ex-post network') is left, and expected total crime will be 0.257, a 0.017 or 6.2% reduction in crime relative to the 'no policy' benchmark.[49]

Now, compare this 'proportional to crime level' removal policy to what would happen if the 'key player' removal policy were to be enforced instead. This is the policy that targets the removal of the criminal whose departure will reduce crime the most. Again, assume for simplicity that the key player will be caught with probability 1. The criminals will then choose a different network structure which is depicted in the bottom-left ('ex-ante') panel of Figure 4. After removing the key player of that structure, we are left with the split network in the bottom-right panel which results in total crime of 0.259. Notice that this number, the resulting total level of crime, is *higher* than that which would result from the 'proportional to effort' policy. The reduction in crime relative to the 'no policy' baseline is therefore smaller.

While it is true that for a fixed network the key player removal policy is by construction the most effective policy in reducing crime, when the forward-looking optimizing behaviour of the criminal organization is taken into account, the resulting network structure may be different. We argue that the policy choice should reflect this. The particular example is simply representative and naturally extremely simplistic. What is important is that the criminals' reaction to the policy (as long as it exists and no matter how constrained) should necessarily be taken into account when choosing the crime-combating strategy. A structural model of criminal behaviour like ours, incorporating the benefits and costs of criminal activity, is therefore indispensable in assessing the effectiveness of various policies and strategies to fight crime or terrorism.

Conclusions and future research

We study the network structures that arise endogenously as a result of the interaction between a deterrence policy and the networked agents' responses in adapting the crime network itself. The 'Lucas critique' that we formalize here in the context of criminal networks argues that using history to forecast the future can be misleading. Outcomes and data from the past are predicated on policies that were present in the past. Therefore, developing current crime fighting policy requires that we understand the behavioural responses to policy at a deeper level than simply observing past outcomes. If there is a

49. The relevant comparison for the expected crime rate is between the no-policy crime level and the post-policy crime level in the ex-post network. The ex-ante network will not be observed as the probability of removal is a certainty. In Easton and Karaivanov, 'The Economic Structure of Crime Networks', we allow for any probability of the policy being effective, ranging between 0 (completely ineffective) to 1 (fully effective).

change in policy, criminals' responses will change too. Our model provides one possible framework that can be used to forecast outcomes when the participants have varying degrees of policy awareness. While this approach has made an important contribution to understanding people's and organizations' behaviour in a variety of macroeconomic policy environments, and we are confident that this perspective is useful theoretically, it remains to be proven as a basis for understanding criminal behaviour.

An important policy-related problem for analysing criminal networks is the lack of or sparseness of available data with respect to their operations or structure. Within the framework of our model, we can study the equilibrium restrictions arising from theory and generate predictions as to how much can be learned about the entire structure from observing only pieces of the network. In particular, we are interested in what is the minimum amount of information (about nodes or links in the network) that would be sufficient to combat criminal activity efficiently.[50] We also plan to investigate the potential usefulness of various summary statistics developed in the literature (measures of centrality, 'betweenness', etc.) in obtaining approximations of total crime activity without knowing the complete structure of the network. Understanding the consequences of a hierarchy within the criminal enterprise is another logical extension to the flat networks discussed thus far.

The networks approach to crime we advocate here is, of course, not without its critics. For instance, Peter Klerks argues that 'sophisticated network analysis methods need to enable investigators to identify positions of power and to attribute these to specific individual traits or to structural roles that these individuals fulfill.' Yet in doing so, he also worries that 'criminologists still need to ask the deeper question about the usefulness of theory for practical applications: if we as researchers come up with "better" knowledge and explanations of empirical phenomena, does this have consequences for the practitioners? Does such criminological research have any relevance and influence on the "real" world?'[51]

Our approach is only partly ready to meet this challenge. There are two things that need to be done to bring it to a point of practical use. First, we need to identify networks and discover whether the parsimonious numbers of parameters we have chosen are useful for predicting the formation of networks and their changing configuration. Second, we need to test whether the underlying model of criminal behaviour is itself a useful one for describing the forces playing on criminals. Is our simple formulation capable of capturing undoubtedly complex behaviour sufficiently well to be useful? In the long run it is important that we confront our model with data. Yet without a model, sophisticated or not, data have no use.

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50. See Dombroski et al., 'Estimating the Shape of Covert Networks', for another approach to identifying missing or hidden links among participants.
51. P. Klerks, 'The Network Paradigm Applied to Criminal Organisations: Theoretical Nitpicking or Irrelevant Doctrine for Investigators? Recent Developments in the Netherlands', *Connections* 24 (2001): 53–65.

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Appendix

In this Appendix we describe our general analytical approach and then solve completely a three-player network example to further illustrate our methodology. EK[52] provide more details for the interested reader.

For a particular network G and choices of efforts of all others, criminal i makes his optimal choice of effort by maximizing the difference between his benefits and costs of crime given in equations (2) and (3). Optimality implies that for each participant ($i = 1, \dots, N$), marginal benefits of doing crime are equalized to marginal costs of doing crime. These are characterized by the first order conditions (FOC):

$$1 + \gamma \sum_{j=1}^{N} g_{ij} e_j = \pi \left(1 + \gamma \sum_{j=1}^{N} e_j + \lambda e_i + \delta \sum_{j=1}^{N} g_{ij} \right) \tag{FOC}$$

For each network of a given number of participants, we solve for the optimal effort level given the parameters. We then search over all possible networks of fixed size N to find the 'optimal' network structure – the optimal G that maximizes network profit.

Formally, if $e^*(G)$ are the optimal Nash equilibrium crime levels that result from a given network structure G, we solve the problem of finding the optimal network, defined as the network G maximizing aggregate profits among all possible networks of a given number of participants.

$$\pi^*(N) = \max_G \sum_{i=1}^{N} \left[y_i(G, e^*(G)) - c_i(G, e^*(G)) \right]$$

Finally, we can extend the analysis even further with what we term 'full optimization', by permitting the number of agents in the network, N, to be also a choice variable. To achieve this, we compare the maximized aggregate profits, $\pi^*(N)$ for various network sizes, N. Depending on the costs and benefit parameters, it could be that small or large networks are optimal – see the discussion in the text.

In the remainder of this Appendix we show how to solve for the equilibrium effort levels explicitly in a simple three-player example. Assume a particular network, G:

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

52. EK, 'The Economic Structure of Crime Networks'.

where G describes the ('full') network in which individuals 1 and 2 and 3 are linked. Use the optimality condition (FOC) to solve for the optimal crime levels, $e^*(G)$:

$$1 + \gamma(e_2 + e_3) = \pi + \pi\lambda(e_1 + e_2 + e_3) + \pi\lambda e_1 + 2\pi\delta$$

$$1 + \gamma(e_1 + e_3) = \pi + \pi\lambda(e_1 + e_2 + e_3) + \pi\lambda e_2 + 2\pi\delta$$

$$1 + \gamma(e_1 + e_2) = \pi + \pi\lambda(e_1 + e_2 + e_3) + \pi\lambda e_3 + 2\pi\delta$$

which is a system of three linear equations in three unknowns to be solved explicitly for $e^*(G) = (e_1^*, e_2^*, e_3^*)$. In this particular example, since G is a symmetric matrix, we obtain a symmetric Nash equilibrium in the optimal individual crime levels:

$$e_1^* = e_2^* = e_3^* = \frac{1 - \pi - 2\pi\delta}{4\pi\lambda - 2\gamma}$$

Of course, we can (and do) solve the problem for every other possible network structure G as well. In the solution for efforts (crime) above, notice that an increase in the direct cost of links (δ) reduces crime as does an increase in congestion costs (λ). Higher benefits from connectivity (γ) increase crime, while higher overall costs (π) reduce it. For the given network, the solution reveals sensible outcomes, exemplifying the general results in the text.