Collaboration and Boundaries in Organized Crime: A Network Perspective

ABSTRACT
A network approach helps us better specify and model collaboration among people involved in organized crime. The focus on collaboration raises the boundary specification problem: Where do criminal organizations start, where do they end, and who is involved? Traditional approaches sometimes assume the existence of simple, rigid structures when complexity and fluidity are the norms. A network approach embraces this complexity conceptually and provides methodological guidelines for clarifying boundaries. Boundary specification in organized crime helps solve four puzzles. First, social boundaries: a network approach reduces confusion about social boundaries as criminal entrepreneurs interact with criminals and noncriminals in diverse contexts, only some of them illicit. Second, boundaries of group membership: network data and methods obviate the need for formal membership attributions. Third, ethnic boundaries: network analyses reveal that the effective boundaries of criminal organizations are based on social relations, not attributes such as ethnicity. Fourth, recruitment: attending to the larger social environments in which organizations are embedded provides a clearer view of how mechanisms of recruitment cross seemingly rigid boundaries between members and prospective members.

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Social network analysis has transformed conceptualization of crime and delinquency over the past 20 years. Criminological theories centered on social factors can now be tested with better data and measures that provide more sophisticated demonstrations of the mechanisms involved. Social network theory and data have provided novel insights, most notably that better understanding of the structure of networks in which individuals are embedded can improve understanding of the intensity of their involvement in crime (Haynie 2001; Papachristos et al. 2011). Social network analysis has been used effectively in a variety of subfields in criminology, including studies of peer influences on juvenile offenders (e.g., Haynie 2001; Weerman 2011; Young 2011) and research on gang violence (e.g., Papachristos 2009, 2013).

The effects of social network analysis on organized crime research have been substantial. “Organized crime” implies forms of criminality that cannot escape the social, in more ways than one. The word “organized” expresses the idea that individuals form social structures of collaboration in order to generate flows of criminal activity. As with other forms of criminality, with organized crime comes secrecy; the higher stakes involved, and the need for continuity, imply a higher form of secrecy in which trust in associates is crucial. Mechanisms of trust—how it is created and what it achieves—are best understood with network data.

How have social networks affected the study of organized crime? Networks initially provided a useful analogy that allowed scholars and practitioners to describe the tendency for criminal groups to be small, flexible, and horizontal in structure. The network approach, however, has proven to be more than just a convenient conceptual tool. It provides both theory and methods and has stimulated important advances in understanding of organized crime. It allows researchers to model the mechanisms that explain recruitment into criminal organizations, the movement of individuals from inside and outside the organizations, and why collaborations occur with some individuals but not others.

A network approach improves specification and modeling of the nature, fluidity, and context of collaboration and of boundaries in organized crime. My focus in this essay is on a particular aspect of networks and organized crime: boundary specification. I propose that boundary specification, delineation of the real (or imaginary) lines drawn between individuals included in a criminal organization and those excluded, can help solve puzzles of collaboration that traditional, nonnetwork approaches...
have not solved. It has been argued, for instance, that the boundaries of criminal organizations are blurry and difficult to determine (Papachristos 2006; Bouchard and Konarski 2014); that criminal organizations tend to recruit both within their own ethnicity and increasingly from outside (Kleemans and van de Bunt 1999; Malm, Bichler, and Nash 2011); and that recruitment follows a snowball pattern (Kleemans and van de Bunt 1999), typically occurring through social ties (Savona et al. 2017). Yet, we do not consider the candidates who were available but not selected through the process.

Traditional organized crime research and data are unable to accommodate the inherent fluidity and porous nature of boundaries in organized crime. A network approach accommodates this fluidity in ways that traditional approaches cannot. It allows us to describe the mechanisms of recruitment, for instance, and allows us to make predictions about who might be recruited. A network approach provides a way to map and organize social interactions among organized criminals. It also provides a theoretical framework within which hypotheses can be formulated and tested. The methodological and theoretical features of the network approach are intertwined. Network data illuminate the contours and nature of the collaborative choices available to organized criminals. Network theory helps us formulate hypotheses and models how collaboration is likely to unfold in specific circumstances.

From a policy perspective, understanding of boundaries is central in targeting organized crime. Most countries have laws that make membership in a criminal organization a crime or an aggravating factor in sentencing convicted individuals. Law enforcement agencies have special units that tackle organized crime and priority lists of targeted organizations. Unfortunately for those efforts, the initial step of specifying boundaries is more challenging than it looks. Drawing the contours of criminal organizations is as much art as it is science, and there is no guarantee that the responsible agencies are using optimal tools to determine those boundaries in the first place. There is a lot of work to be done in understanding boundaries and collaboration in organized crime. A network approach, while not without limitations, is especially well-suited for the job.

I focus on aspects of network data that are salient to organized crime; not all network applications make the approach unique or necessary. I focus on subjects concerning which network data offer a particularly powerful approach for improved understanding of organized crime paradoxes...
or puzzles that network data can at least partially solve. Network analysis and data, of course, are not the only useful approach. For instance, economic theories of organized crime bring a unique set of conceptual and analytical tools that shed light on the dynamics of illegal markets (Reuter 1983; Kleemans 2014). Given the right context, the enterprise model of organized crime makes assumptions about the nature of micro co-offending decisions in criminal conspiracies that overlap nicely with network models of organized crime (Haller 1990). Without context, networks may not be useful, especially in organized crime networks in which status differentiation among network members influences their relations (Calderoni 2012; Varese 2013; Campana 2018).

I am not the first to propose the value of network methods, at least broadly speaking, for criminology as a whole (Morselli 2009; Carrington 2011; Papachristos 2011; Bouchard and Malm 2016; Campana 2016a; Galupe 2016; Gravel and Tita 2017; Ouellet and Hashimi 2019), or even in organized crime (Sparrow 1991; Kleemans and van de Bunt 1999; Morselli 2005; Bouchard and Morselli 2014). Bouchard and Morselli (2014) argued that a network approach allows us to appreciate how large groups can emerge but not necessarily operate, function, or behave as a large group when crime-to-crime co-offending interactions are considered. They used the term “opportunistic structures” to describe these smaller clusters of individuals working together under the umbrella concept of organized crime.

Yet, despite advances in the use of network analyses in organized crime, and constant growth in the number of scholars adopting network methods, the approach has neither transcended the field nor become a staple in criminology research. One of my aims is thus to demonstrate how networks help us make otherwise impossible advances. A difficulty for efforts to understand collaboration in organized crime is that relationships are multiplex, and networks involve both noncriminals and criminals, sometimes at the same time. Using networks as an organizing principle can help make sense of the various ways in which organized criminals interact and collaborate. When that happens, some of the contradictions that exist in scholarly and law enforcement representations of organized crime can be diminished.

In this essay I discuss four unresolved puzzles of boundary specification in organized crime. First, I consider the social boundary problem, showing how a network approach can reduce confusion as members in-
teract and collaborate with outsiders. Network researchers do not always have access to data extending beyond the criminal network (e.g., co-offender networks), making distinctions between the criminal and the social impossible. Yet, when data on diverse types of interactions are available, a network approach can handle this complexity. Second, I turn to the boundaries of group membership per se, illustrating how the use of network data and methods can obviate the need for formal membership attributions, at least prior to establishing the social structure based on demonstrated social interactions among criminals. Third, I consider the ethnic boundary problem, showing that a tendency for ethnic homophily—the tendency for individuals to connect with others with whom they share characteristics—within criminal organizations does not necessarily make it a suitable descriptor of types of organized crime: the effective boundaries of criminal organizations are first measured by social relations, not attributes like ethnicity. Using relations as a starting point allows us to see the variety of individuals with different ethnic backgrounds in particular organizations. Importantly, a network approach can establish that organizations may be ethnically diverse, but that their members may still display a preference for connections to members of their own ethnic group. Finally, I cover the seemingly rigid boundary that separates current members and outsiders who might be recruited. I show how broadening the view of recruitment to the larger social environment in which the organization and its potential recruits are embedded can provide a clearer view of the mechanisms involved, including recruitment within the organization for specific criminal ventures.

Here is how this essay is organized. Section I provides conceptual background for readers for whom network approaches are a new subject. The network approach is both theory and methods. Any form of organizational structure can be investigated with network data, not only those characterized by horizontal partnerships. Section II, the bulk of the essay, discusses the four boundary specification problems described above. Section III discusses dangers of a network approach: overinterpretation, overcomplexification, and oversimplification. Section IV discusses underdeveloped subjects of which better elucidation may answer remaining puzzles: how and when boundaries form, analyzing organized crime networks over time; variations in cultures of collaboration; age boundaries, collaboration across age groups; and geographical boundaries, analyzing transnational networks. Section V concludes.
I. A Network Approach to Organized Crime: Conceptual Clarifications

There are key conceptual distinctions that need to be made before we jump into the crux of the argument. First, what does it mean to say that a network approach is both theory and methods? Second, are networks and organizations opposite ends of the organizational spectrum? In other words, can we use networks to study criminal organizations that have clear role and relationship hierarchies?

A. Both Theory and Methods

“Social network analysis” refers to the set of methods used to derive meaning from social interactions (Wasserman and Faust 1994). Network approaches come with distinctive research designs that involve novel ways to generate data (e.g., the use of name generators), to code (e.g., at the dyad rather than the individual level), and a suite of techniques and measures to choose among when describing networks. It is an intellectual world of its own, and easy to get lost in. But social networks are also highly intuitive. We are all embedded in them, and though we vary in our capacity to see, or desire to reflect on, the implications of the structures of our own social networks, network analysis and its methods becomes familiar and rewarding once terminological hurdles are crossed. Many network techniques may be new in a technical sense, but ideas about social networks influencing behavior go back a long way, including Simmel’s (1955) important theoretical work on why individuals form groups and how groups (or social circles) interweave in communities of conflicts and affiliations.

Because of the effort required to learn techniques and measures, it is easy to frame social network analysis as a set of methods. These methodological tools are not, however, independent of theoretical underpinnings. Instead, network methods are typically packed with theoretical assumptions, the most fundamental being that social relations influence behavior, attitudes, or both (Knoke and Yang 2008; Borgatti et al. 2009). Social relations are mapped, and locations of individuals in networks are examined because this influence on behavior is assumed to matter. The interdependence of people is fundamental; the actions of one are assumed to affect the actions of others connected to them, sometimes even if this connection is indirect. This interdependence is inconvenient for traditional statistical approaches to crime data, which assume independence of observations. Network approaches embrace interdependence by find-
ing meaning in it (Papachristos 2011). Exponential random graph models (ERGMs), for example, are a type of logistic regression model in which special parameters, such as transitivity (a friend of my friend is also my friend), are included to estimate the effects of interdependence among people, groups, or organizations to explain a network’s structure—who connects with whom, and why (Lusher, Koskinen, and Robins 2013).

Part of what makes the network approach also a “theory” is that use of these data cannot be detached from those assumptions. The mere linking of nodes brings to light the main theoretical mechanism of the network approach, namely that a variety of phenomena can be explained by examining the transmission of objects, sentiments, or information from one node to another. It is not, therefore, a single “theory” but a set of assumptions and principles from which theory can be specified. Typically in the social sciences, network data about individuals (how many connections are they brokering) are used to theorize about a nonnetwork outcome (how much money do they make?) (Morselli and Tremblay 2004). Social capital theory, which emphasizes abilities to use social relations to gain advantages, is a common example (Lin, Cook, and Burt 2001). That social capital is theorized or operationalized using networks is important because the theorized mechanism underlying the pursuit of an advantage is assumed to emerge from the transfer of information, knowledge, and sentiment through connections among individuals. Not all individuals are equal in their ability to use their social connections, and those differences may affect the relative advantages they obtain. This is the point of departure of numerous network studies.

This dual role as theory and methods is why I use the term “network approach” in this essay, to encompass the array of roles that networks play in understanding of phenomena such as organized crime. Adopting a network approach implies study of phenomena using network data and using network theory to interpret patterns that are found. Users of those methods do not always realize this. To say, for instance, that a “high betweenness score” is indicative of power,” or to focus on the measure for making distinctions in data, is tantamount to applying a network theory hypothesis that individuals who score higher matter more than others.

1 Betweenness centrality is a network measure that captures the number of times an individual is found in-between two others, who are otherwise not connected. It is a relatively popular measure among crime network scholars because brokers—a common label for those who score high on this measure—have been shown to be key elements of networks in various illicit contexts, including for disruption purposes (Morselli 2009).
They may have more information, knowledge, or access to resources, or all these desirable attributes at once. It is essential for network scholars to think about the theoretical ramifications of the measures they use in interpreting their findings and to be explicit about the theoretical mechanisms implied in their interpretations.

**B. Networks, Groups, or Organizations?**

There is some confusion concerning whether networks are a distinct organizational form, one that would sit at the lower end of the spectrum of levels of organization (von Lampe 2009; Campana 2016). In this view, networks describe small, loose “disorganized” partnerships, an organizational arrangement starkly different from hierarchical organizations such as the Italian mafias or outlaw motorcycle groups such as the Hells Angels. This representation of networks as a type of organization may have emerged from a growing realization in empirical studies of organized crime that criminal partnerships are much less formal, rigid, and lasting than was long assumed.

Though it can have value in when terms are clearly defined (e.g., Powell 1990; Podolny and Page 1998; Campana 2016), this characterization of networks should be resisted. As an approach, network analysis does not discriminate between hierarchies and loose partnerships; networks can describe groupings of any kind. The essential condition is that the grouping involves social interactions among its members. Von Lampe (2003, 2009) aptly summarizes the status of the network approach as generalizable to any type of organization in this way: “The alternative to such a one-dimensional view is to treat networks and organizations as representing distinct structural dimensions while acknowledging that networks and organizations are not empirically independent. Organizations evolve out of and are transcended by networks, just as every organization can be defined as a network because its members are by definition connected through specific ties” (2009, p. 96). I insist on this because it is easy

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2 Crime network scholars would benefit from testing the assumption that “brokers do better” more often (Morselli 2010). I suspect that many network brokers ignore their positional advantage and are unsuccessful at obtaining tangible benefits from it. I come back to this idea below when discussing the dangers of overinterpretation.

3 “Networks as a form of organization” is also a subfield of research in organizational sociology that tries to capture the more informal, trust-based arrangements falling in-between hierarchies and market forms (Powell 1990; Nohria and Eccles 1992; Podolny and Page 1998).
to miss differences in the context of relations for network analyses that do not include contextual information on the nature of ties between individuals. We could wrongly conclude, for instance, that two groups function similarly because they have similar network structures. In some cases, this would be correct. In other cases, however, we would miss that the network effects of hierarchical relations exist only because of the hierarchical context in which they are embedded. In other words, the structure may be the same, but the qualitative nature of ties is different. Ultimately, this highlights a pitfall of network data as a sole source for assessing organizational structure: unless the data include contexts, it may operate at a level that is too abstract to reveal network differences across groups, even when differences exist.

The differences would not be in network structure, but in the mechanisms that allow the network structure to emerge. Statistical methods such as ERGMs can answer questions at the heart of collaborative organized crime structures such as whether a member’s ranking, or other attributes such as ethnicity or age, are important drivers of connections in the network (Ouellet, Bouchard, and Hart 2017). These models can examine whether homophily is a driver of connections. For instance, Smith and Papachristos (2016) tested an ERGM on Al Capone’s network, finding that ethnic homophily existed in his personal and criminal networks but not in his legitimate network, where homophily was a negative predictor. ERGMs also allow for controlling for behaviors that may exist in any network, criminal or otherwise, such as transitivity, the tendency to become friends with friends of our friends, or to reciprocate ties. That way, confounding network processes can be controlled for, and the results can be assessed at face (statistical) value. We can ask whether rank is a driver of connections, whether some hierarchies behave differently than others, while controlling for other variables like ethnicity and age that might be relevant to these ranks and hierarchies. This allows testing of specific hypotheses related to recruitment, but also to promotion within criminal organizations.

Network data, then, are ideally suited to describe both formal and informal groups. They can also illustrate the different ways in which organizational style influences the nature and structure of social relations (Erickson 1981). The subcultural context in which networks are found is an important source of influence on the structure of social ties, and the nature of collaboration within criminal organizations, ideas I develop further below.
II. Collaborative Ties and the Problem of Boundary Specification

Criminal “collaboration” refers to individuals working together to produce a criminal outcome. Thus, it excludes scenarios in which two individuals, who otherwise may be “criminals,” collaborate in legitimate pursuits. The term criminal labels the activity and the context, but not the individuals involved. Collaboration, as I use the term, serves as a generic, umbrella concept\(^4\) that encompasses other terms including collusion, conspiracy, co-offending, or cooperation. Using the term collaboration excludes the role of networks in understanding conflicts among criminal organizations. Network data have shown their value in understanding conflicts among street gangs (Papachristos 2009; Descormiers and Morselli 2011; Bichler et al. 2019), but have less often been used to examine patterns in conflicts in other types of groups.

An unintended consequence of adopting a network perspective on collaboration in organized crime is to broaden the view of the unit of analysis. Following the connections among offenders, as a general approach, implies that a diversity of individuals and affiliations in the process will be observed, in contrast to a narrow view of organized crime as represented by mafia families or cartel members in Mexico or Colombia. If criminal organizations go outside their immediate members to collaborate with other criminal entrepreneurs, following connections makes the integration of those outsiders almost unavoidable. This does not mean that the network should be allowed to grow infinitely, until distinctions between organized crime and other criminals disappear entirely. There are numerous qualitatively important differences between the minority of organized criminals and others, including cultural ones (Paoli 2002; Varese 2010) that even a network approach will want to emphasize. Yet, in the end, use of the network approach lets us consider both organized crime and other criminal entrepreneurs as belonging to the same social environment. Because the network of collaborations in organized crime typically includes a diverse range of criminal entrepreneurs, some of whom are independents not affiliated with criminal organizations (Morselli, Paquet-Clouston, and Provost 2017), I use similarly broad lenses to

\(^{4}\) Co-offending, for many, narrowly refers to specific crime events found in police data. Not all collaborative relationships are conspiracies, and, as a specific type of conspiracy, collusive situations are relatively rare when compared with other collaborative behavior in organized crime.
approach the topic. Case studies I discuss and terminology I use reflect this diversity.

Study of collaboration in organized crime necessarily raises the issue of boundary specification. Following collaborative ties among offenders naturally leads to difficulties of characterization: Are all of these contacts part of the criminal organization? Where does the organization stop, and where does it end? In their seminal work on boundary specification, Laumann, Marsden, and Prensky (1983) argued for group boundaries to be approached using a realist strategy, in which boundaries are based on the perspective of members themselves, or a nominalist approach, in which boundaries are specified according to the researcher’s analytical framework. The realist strategy is limited to the extent that it requires members to have a shared conception of the group and to be aware of the full extent of the group’s composition or operations, relying on the implicit assumption that a natural boundary exists—two conditions that are hard to find in criminal contexts (Ouellet and Bouchard 2018). In contrast, the nominalist approach uses the theoretical questions being examined by the researcher to define group boundaries. The framework favored by Laumann, Marsden, and Prensky (1983) in setting group boundaries is the social network approach. Boundaries, where they exist, should first be set from patterns in social interactions. At the same time, the attributes of individual actors can and should be used to provide context for the interactions in the first place (Ouellet and Bouchard 2018).

In this section, I examine four areas in which a network approach to collaboration in organized crime helps provide a better understanding of boundaries. The first is the difficulty in both social and criminal contexts of determining “membership” in criminal organizations. The second concerns group membership—who is a member, who is an outsider, and how do we tell the difference? The third is ethnic boundaries, whether they exist, and how network data help move away from ethnicity as a type of organized crime. Finally, I discuss recruitment, how and when outsiders cross the initial boundary into the world of organized crime.

A. The Blurred Social and Criminal Boundaries in Organized Crime

Organized criminals do not make it easy for researchers to identify clear boundaries between people involved in their criminal activities and people

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5 This paragraph draws from a similar argument on group boundaries in Ouellet and Bouchard (2018) in the context of a terrorist group.
who are material to other parts of their lives. They manage their social and professional lives as we all do, not drawing clear, hard lines between the different spheres of their lives. Individuals from one sphere may intersect with individuals from another: people who met at work may cross paths with other friends and family members; coworkers may become friends; existing friends may be hired in your workplace. Not all coworker conversations involve the personal details of our lives. Not all coworkers are invited to dinner in our homes. Some are; those are not only friends or coworkers, they are both. But not necessarily at the same time; the two roles don’t have to occur simultaneously.

Consider two independent criminal entrepreneurs in their mid-30s, Thug and Veteran, each an object of heightened law enforcement attention. Looking at 8 years of police data, Hashimi and Bouchard (2017) found that 50 percent of a network looked like law-abiding citizens. The data included any interactions recorded in police files. Many were not criminal: a speeding ticket, a sobriety test, a surveillance report. Sometimes a frequent accomplice was observed sitting in the backseat of the car, with Thug in the passenger seat, and Thug’s wife driving to a local restaurant. Two of the three were otherwise involved in criminal conspiracies, but neither the context nor the behavior was criminal. There is no reason to assume all the participants are members of a criminal group, at least based on only this information.

Penetration of the grey area between criminal and social associations is much easier with a network approach. It acknowledges that relationships have multiple layers. It need not apply a permanent label to individuals, such as whether they are or are not a member of the organization. Its focus on relationships and their context allows the flexibility needed to accommodate complex (or “multiplex”) relationships.

Much of the difficulties in disentangling family and criminal ties within Italian mafias, for example, can be illuminated with network data. Paoli (2002) highlighted how elements of Italian culture complicate mafia relations in ways that do not reflect clear-cut boundaries between the criminal and the social. Paoli observed that relationships within Italian families are often mischaracterized. It is a mistake, for example, to assume that most interactions within a particular family involve criminal conspiracies. Leadership does not equate to control (Mastrobuoni and Patacchini 2012). Attendance at events does not imply membership in a criminal organization (Calderoni, Brunetto, and Piccardi 2017). Conflating the family unit with a criminal organization is a mistake; families play cultural roles that
cannot, at least from the outside, be easily distinguished from criminal activities (DellaPosta 2017).

A network approach can disentangle family and criminal organization links conceptually and empirically. In network jargon, those relationships are multiplex ties: relations among individuals that are actualized in a variety of contexts. When observed together at a funeral, Al and Nick are friends. When sitting in a café the next day, they may be organizing the next cocaine shipment, making them co-offenders. When they play football that evening, they are teammates. Their relations are multiplex; together, they share three networks: social, criminal, and athletic. The criminal network may be examined by itself, or it may be combined with other networks into a generalized “social network” that includes diverse social interactions. The more network contexts two individuals share, the closer they are assumed to be (Verbrugge 1979).

Network researchers often lack access to more than the criminal network, making distinctions between the criminal and the social impossible. Yet, when data on multiple types of interactions are available, a network approach can easily handle this complexity. Crime and social worlds may be more intertwined in organized crime than in other settings because of the importance of trust (von Lampe 2003; Smith and Papachristos 2016; DellaPosta 2017). Criminal ties can be examined separately from social ties when the aim is to examine collaboration in criminal conspiracies. Both types of ties can be considered together when the aim is to understand the interplay between the social and criminal: How much do organized criminals co-offend with individuals with whom they socialize?

Think back to Thug and Veteran, two individuals who saw themselves as independent criminal entrepreneurs (Hashimi and Bouchard 2017). Their social and criminal worlds were fully intertwined, making it nearly impossible to distinguish where the criminal started or the social stopped. The 101 contacts between them over 8 years of data involved seven recognizable communities or subgroups, which covered 80 percent of the total contacts (20 percent were one-offs or did not involve enough interaction with others to constitute a subgroup). Five of the seven subgroups included mixes of individuals who did and did not have a criminal record; only one group of four individuals qualified as a 100 percent crime clique. All seven subgroups were formed from the accumulation of social interactions; very few explicitly co-offending interactions were recorded.

Thug and Veteran interacted with individuals who were members of criminal organizations. Veteran grew up with four people who became
members of an outlaw motorcycle gang. They were part of a subgroup of close friends that included Veteran’s law-abiding family members. None of those interactions between bikers and family members were criminal in nature, but it would be easy to miss this without data on the contexts of interactions.

Smith and Papachristos’s (2016) work on Al Capone’s social network provides a clear example of how a network approach can help distinguish between the social and the criminal. They collected rich data on every identifiable individual who could be found to have interacted with Capone during his lifetime and beyond (ca. 1900–1950). They differentiated between social ties with friends, observed to have occurred in purely social contexts; criminal ties observed in the context of actual crimes and conspiracies; and legitimate ties that emerged from interactions in purely legitimate contexts. Figure 1 shows a subset of Capone’s network; thicker
lines indicate the number of different types of ties connecting individuals. Relations are not equal, which provides a first layer of understanding about the relative strengths of relationships among people connected to Capone.

Figure 1b extracts four nodes from figure 1a, Capone (1) and three of his closest criminal associates from the Hawthorne Kennel Business Club, Guzik (5), Levine (7), and Libonati (8). It illustrates variations in contexts in which they interacted. Capone shared a friendship with all three. Libonati and Capone’s relationship included political support and legal advice, but never a criminal association. Within the club, only Levine received legal advice from Libonati, but their relationship stopped there. It did not have other layers as did Libonati’s with Capone.

A network representation such as is shown in figure 1a, which includes all possible types of links between individuals around a crime personality like Capone, appears to indicate that it is of one close-knit criminal group, but it is not. Libonati and others such as Serritella would have to be excluded. The point is that they can be excluded from the criminal group, but included in the more general network representation, because relations were coded, not individuals. With a network approach, relations of particular types can be included or excluded when analyzing networks
for different purposes. Networks are built from relations between individuals (the lines—or edges—we see in networks). Figure 1c, which separately shows the larger criminal network (left) and the family and friendship network (right), demonstrates how these two types of links can be examined as the separate networks they are.

Networks that focus solely on criminal ties between individuals, for example, co-offending networks, miss the larger social environments in which criminals are embedded. These other network members are important because they may be candidates for inclusion in a future criminal conspiracy and, even if that never happens, they may influence decisions of members of the organizations and thereby shape network structure (Ouellet and Bouchard 2018). The last point is not trivial. Noncriminals are part of organized criminals’ social worlds because they influence decision making; this is crucial in an approach that assumes that social relations are the most important source of influence in human behavior. Crime network scholars do not always take full advantage of the power of network data.

B. A Network Approach to the Boundaries of Group Membership

Although it is tempting to rely on formal membership attribution data to study criminal organizations, the literature on organized crime networks has shown that this can be misleading (Morselli 2009). Law enforcement

Fig. 1c.—Capone’s criminal and personal networks. Source: Smith and Papachristos (2016).
agencies, in particular, may find it hard to resist the temptation to follow membership data, especially in investigating RICO-like cases. Limiting information to formal members, however, truncates their social worlds unnecessarily. Morselli (2009) showed, for instance, that high-ranking members of Nomads Hells Angels of Montreal were embedded in vast networks of associates of all ranks, including many nonaffiliated individuals who played important brokerage roles. Years before, Morselli and Giguère (2006) showed that legitimate actors played quantitatively and qualitatively important roles in a major drug importation network. Clearly, a broader approach based on social interactions is warranted.

Some criminal organizations like the Hells Angels or the Italian ‘Ndrangheta have systems of ranks that make it relatively easy to count their members. There is little need for network data to discover the size of an organization if the number of capos or, in outlaw motorcycle gangs, “full-patched” members can be learned from police investigation techniques and intelligence data analysis. For other types of organization, a majority of criminal groups (Bouchard and Morselli 2014), network data are needed to distinguish members from casual “guests.”

For more formal organizations, network data serve a related purpose, notably to understand the relationships across ranks (Morselli 2009; Calderoni 2012). This information is useful for multiple purposes, including prediction of promotions, understanding the structure of cooperation within the organization, and examining recruitment for specific ventures and conspiracies.

An important assumption of a network approach is that patterns of interactions among criminals provide a foundation for determining common membership in a recognizable social grouping. Membership, as I use the term here, involves its least restrictive meaning—belonging to a recognizable group—and does not imply or refer to a formalized membership process. Network data and methods facilitate identification of subgroups within criminal networks based on a clustering of interactions that is denser within the group than outside of it. The distinction between formal membership and informal subgroup membership becomes less salient. People who are assumed to be part of a group are not necessarily people who explicitly say they are members or who committed at least one crime with the group. Instead, members of network-based subgroups have interacted often enough with a set of individuals to belong with those individuals and not others (Laumann, Marsden, and Prensky 1983). In other words, subgroups need to be relatively cohesive to be labeled as
such. First consider the social structure shown by interactions among individuals. Formal attributions, if necessary, can wait until that first step is completed.

Ouellet, Bouchard, and Charette (2019) provide a blueprint for using network data on subgroup membership attribution. We extracted subgroups from among a large network of individuals who came into contact with police via arrests and noncriminal police interactions over a 10-year period. The starting point was 261 individuals confirmed to be gang members by use of a combination of police investigation records and ethnographic data. In the spirit of snowball sampling designs, these seeds, their contacts, and the contacts of these contacts made up the full network of 6,604 individuals. Though the 261 seeds were members of so-called Haitian gangs, among the 6,604 connected to them were members of outlaw motorcycle gangs and members of so-called Italian mafia organizations based in Montreal, among others. Subgroups were extracted using a commonly used method in network analysis (the Louvain method; see Blondel et al. 2008) that divides the network into an optimal number of subgroups (communities) based on individuals’ patterns of interactions, seeking out local clusters of high interconnectivity. The algorithm first detects subcommunities within the network based on members who have more dense connections with each other than with other members within the network and then proceeds to build a network at the subgroup level, consisting of connections between the subgroups detected in the first step.6

Applying this method, we identified 327 subgroups of individuals that averaged 18 members. Importantly, not all individuals in these groups were connected to each other, and not all their connections were found within their assigned Louvain group. This allowed us to examine variations in groups’ tendencies to connect within and outside their group, and whether those characteristics were associated with group survival.

To assess survival, we divided the 10-year period in three, so that “survival” implied a stable set of interactions among members for over

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6 By comparing the proportion of ties within communities to the proportion of ties between communities, the Louvain algorithm aims to maximize the modularity score, which is equal to zero when there are no within-community ties and equal to one when all ties are within the community, with higher values indicating better fit (Newman and Girvan 2004). Dozens of different classification methods are available in network analysis software. The algorithm for each differs depending on the objectives of the classification.
4 years. Less than 20 percent of the qualified groups were sufficiently stable to be found in at least two periods, and only 6 percent existed for nearly 10 years. Survival was a function of group cohesion, but the relationship was not direct; it was moderated by group size. For small groups, alliances outside the group were key to their survival. The opposite was true for the largest groups: the more alliances outside the organization, the less likely they were to survive. In short, large groups that adopt closed structures are more likely to persist, while survival of small groups depends on less cohesive and more versatile structures. Importantly, none of these hypotheses could have been tested without network data and its capacity to handle, and measure, the complex interplay of connections within and outside criminal groups. Traditional approaches often choose between units of analysis (the “group” or the “individual”). A network approach gets closer to the reality of these groups; their boundaries are bound to be more porous than most nonnetwork analyses can handle.

The lesson learned, and the way forward for organized crime scholars and law enforcement agencies, is to reverse the usual order in which things are done, with a twist. First, establish the social structure of interactions among organized criminals using network data and methods. Second, apply formal membership data on top of the structure uncovered with network data. The twist: the first step requires a relevant starting point, and it could very well be that the optimal starting point requires formal membership data. The networks we analyze capture a portion of something that exists in real life, but they are constructed with partial data (i.e., a biased sample of all interactions that occurred) for research purposes. The process of network construction follows universal, relatively standard, rules of coding, but any such exercise still entails sometimes arbitrary decisions about where to start. Smith and Papachristos (2016) started with Al Capone; Hashimi and Bouchard (2017) with the top two criminal entrepreneurs based on the local police detachment; Calderoni, Brunetto, and Piccardi (2017) with confirmed mafia meeting attendees; others go with all individuals named in organized crime investigations (Morselli 2009; Malm and Bichler 2011; Tenti and Morselli 2014). In all those cases, the relevant starting point was provided in the form of an attribute that may have required qualitative data on membership.

Calderoni and colleagues’ (2017) work on the structure of ‘Ndrangheta networks exemplifies how that approach may be applied to answer both
policy and empirical questions. They analyzed investigative data coming from 574 mafia meetings that, combined, included 256 individuals. Attendance at a meeting was used as the basis for a connection in the network. They used a community detection algorithm similar to that used by Ouellet, Bouchard, and Charette (2019) to extract subgroups from the meeting data. Importantly, membership to these subgroups could be directly compared to known formal membership data from criminal intelligence—groups known as locali. The 17 locali were structured into seven distinct communities; this means that many members of locali had such close and frequent connections that, for all intents and purposes, they belonged to the same locali. In short, the geographically and culturally informed distinctions made by mafiosi on locali membership only partly matched their network behavior. Arguably, each of the approaches to describing the social structure of the ‘Ndrangheta is informative in its own right. Yet, the additional insights provided by network data (which locali are close enough to belong to the same community) are hard to overlook.

The study provides one more useful demonstration for my purposes: the identification of mafia bosses from network data. Police data revealed that the 254 individuals who attended meetings included 34 bosses. The networks were not constructed with these bosses used as seeds; instead, all meeting attendees were included. Yet, the formal mafia boss attribution can be applied after the fact to examine whether bosses are positioned differently in the network. Calderoni, Brunetto, and Piccardi (2017) found that the 34 bosses were the brokers in the network. They were not only important within their own communities; they were also the drivers of connections between communities. Many attend local meetings, but only a few select individuals act as representatives of their locali outside its geographical boundaries. By combining these patterns, Calderoni and colleagues were able to predict who the bosses were with near-perfect accuracy.

What remains unsolved from pure network-based groupings, as clear-cut as they seem from a data point of view, is whether these boundaries carry meaning for their members. There are at least two situations that could arise. First, group members might disagree with their attributions, pointing out, hypothetically, that their frequent interactions with a set of individuals do not carry sociological meanings associated with group membership. Second, members might not think in terms of group membership at all; they might think of themselves as collaborating with others, sometimes frequently, but disagree that a layer of group membership should be added to these collaborative relationships. Network scholars might argue
that group members’ perceptions are a matter of awareness, that if they act or “interact” like a group, they can be considered as one. But we should be cautious in interpreting these groupings as material, especially without support from observational or interview data. A boundary may exist in the data, but not in the minds of the individuals involved.

**Among Members, Who Is Part of the Core?** There are a few boundaries to consider even within criminal organizations. Though a network-based group would be characterized by a higher degree of cohesion within it than outside of it, this group may adopt structures that sometimes vary widely. For example, these structures can be described as varying between centralization (a few individuals responsible for the bulk of connections) and decentralization (connections are more evenly spread), which will affect the relative efficiency of collaboration. Centralized and decentralized structures also affect their vulnerability to disruption (Malm and Bichler 2011; Joffres and Bouchard 2015). Interventions into centralized networks have little effect on peripheral actors who make up the majority of members, but can be devastating if they affect individuals in the center. Conversely, interventions into decentralized networks are more likely to involve individuals with relatively many connections; removal of any one them is unlikely to have large overall effects on the network.

A key boundary within criminal organizations, if one exists, is between the core and peripheral members. The distinction is important to law enforcement agencies that want to disrupt networks. If an organization has a core, and agencies can identify it, targeting the core may affect the organization’s capacity to recover. Membership in the core plays a symbolic role; it indicates prestige, achievement of a rank members aspire to, being part of an inner circle with influence over other group members, and authority over organizational decisions.

From a network perspective, a core-periphery structure exists when a handful of members have a high degree of cohesion, while the vast majority of others interact very little, though slightly more often than with members of the core (Borgatti and Everett 2000). If all members display

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7 The importance of the core relies on the assumption that its members carry out the most important network functions and are thus difficult to replace. Campana’s (2016b) analysis of Nigerian human smugglers shows that this is not always true. The most important actors, the least easily replaceable, were madams at the periphery (also see Zhang, Chin, and Miller 2007). Without their recruitment skills, none of the core activities could take place.
high cohesion with other members, or if the core consists of a majority of members, the organization lacks a core-periphery structure. Figure 2 illustrates a simple core-periphery structure in which nodes 1–4 form the core, and the remaining nodes constitute a disconnected periphery. A network approach can improve understanding of whether a criminal organization has a core.

Bouchard and Konarski (2014) used this approach to determine whether a young gang loosely affiliated with the Hells Angels had a core, and whether a police attempt to remove the gang’s core had identified the right individuals. Six members whom police targeted were surrounded by 54 others who had at least one connection to the targeted six. The 60 individuals formed a network with a core-periphery structure in which 13 formed a dense core. Five of the targeted six were part of that core, but many were missed, including one with the highest “coreness” score (Bouchard and Konarski 2014). The group survived and became a well-known criminal organization in western Canada.

The existence of a core set of members in a criminal organization indicates a culture of collaboration driven from the center out. Other

![Fig. 2.—A network displaying a simple core-periphery structure. Source: Author.](https://example.com/network-diagram.png)
collaborative structures exist within organized crime, including small-world structures (many highly connected subgroups linked by a few bridging ties, making any actor reachable in only a few steps; Malm and Bichler 2011) and cellular networks distributing illegal commodities across borders (Bruinsma and Bernasco 2004). No matter what the structure, network data allow more precise identification of group boundaries and have some value for understanding collaboration within and across those boundaries. And network blockmodeling techniques (i.e., grouping units based on network equivalence), like core-periphery analyses, allow examination of elements of the structure of organized crime boundaries that are impossible with other techniques.

C. Networks to Investigate the Ethnicity Boundary

Ethnicity-based classifications of organized crime have remained staples of criminal intelligence agencies. Italian-, Asian-, and Mexican-based organizations are found in the classifications of agencies around the world and in textbooks; many add eastern European, African, and Middle Eastern gangs to the mix. These labels may be appropriate when discussing local organized crime phenomena, but not in classifications of types of organized crime.

There is investigative convenience in use of these classification schemes, especially when information is hard to come by. Ethnicity may correlate with distinct illegal market behavior, such as the use of particular smuggling routes or sale of particular drugs. Classification by ethnicity is also compatible with homophily—the tendency of individuals to connect with others similar to them (McPherson, Smith-Lovin, and Cook 2001). Ethnic homophily is a strong driver of connections in social networks, criminal or otherwise (McPherson, Smith-Lovin, and Cook 2001; Hughes 2013; Grund and Densley 2015; Kreager et al. 2017). The notion that these tendencies found in almost any social networks exist in organized crime networks is not, in and of itself, controversial.

The problems raised by use of ethnicity classifications outweigh their benefits (Kleemans and van de Bunt 1999; Bovenkerk, Siegel, and Zaitch

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* For instance, Dubro, Champlain, and McAdam (2019) treat “multiethnic gangs” as a category on its own. Malm et al. (2011) show the lack of predictability of these classifications in matching network behavior, as shall be seen below.
Using ethnicity or race as a driver of police priorities creates human rights violations that have no place in the criminal justice system. These classifications can create dangerous oversimplifications in building cases against offenders of a particular ethnicity, regardless of their involvement in organized crime. Belonging to a criminal organization is a common aggravating factor in sentencing in many countries. Ethnicity alone may be used as a justification for targeting individuals, rather than targeting illegal behavior. Ethnicity by itself is a weak basis for distinguishing types of organized crime. Many people in organized crime are involved in supply of commodities in illegal markets. Almost any ethnic group an agency considers targeting is involved in illegal drug and other markets. Use of ethnicity as an overarching classification of organized crime is counterproductive.

A network approach can shed light on ethnicity boundaries and develop theoretically and empirically sophisticated descriptions of the ethnic composition of organizations. Inside the organization, a network approach can examine the association between ethnicity as an attribute and links between individuals who share that attribute. McCuish, Bouchard, and Corrado (2015), for example, describe a sample of 18 individuals taken from a larger criminal group of whom 50 percent were Caucasian, close to 40 percent were Asian, and the rest were Middle Eastern. Members collaborate within and across ethnicities (Tenti and Morselli 2014; Campana 2016b, 2018), even though tendencies for homophily often make collaboration within ethnicity more likely (Grund and Densley 2015).

From a network perspective, the question is not whether gangs and criminal organizations have ethnically varied memberships; they do in places where the general population is diverse. Ethnic composition is more homogenous in mafia families and in organizations such as the Hells Angels, especially if only made men or full-patched members are considered. Compositions vary in diverse ways. To understand the diversity, the effective boundaries of criminal organizations should first be assessed in terms of social relations, not attributes such as ethnicity. Social relations are a starting point for observing the variety of ethnicities in a particular organization. Using ethnicity to chart membership can cause diversity to be overlooked. Organizations may, for example, be ethnically varied, but their members may nonetheless prefer connections to others of their own ethnicity. Those are important subjects, understanding of which can be illuminated using network data and methods.
Some of the most compelling evidence about the role of ethnicity (or, often, nationality) is provided by Paolo Campana. His studies are based on network-specific models called Quadratic Assignment Procedure regression. He investigates whether being from the same ethnicity is associated with network connections. Neither transnational human trafficking networks organizing transport and exploitation from Nigeria to Italy (Campana 2016b), nor the migrant smuggling network operating across the Mediterranean (Campana 2018), showed evidence of homophily based on nationality. In the human trafficking network, nationality was a significant negative predictor. Traffickers were more likely to connect with others from different nationalities.

Ethnic collaboration across criminal organizations has also been studied. Malm, Bichler, and Nash (2011) looked at co-offending associations among criminal organizations in British Columbia. Figure 3 shows intelligence data on co-offending among organized crime offenders. The data are aggregated at group level (if an offender from group A co-offends with an offender from group B, groups A and B are assumed to be connected), using intelligence agency categories: outlaw motorcycle gangs

Fig. 3.—Co-offending between groups in British Columbia, Canada, circa 2007. Source: Malm, Bichler, and Nash (2011).
(dark circles), Asian groups (squares), Indo-Canadian groups (light circles), unclassified groups, and individuals not known to belong to any group (triangles).

Figure 3 shows co-offending connections at the group level. There is a high level of connectivity across groups. Distinct clusters of similar nodes linked together in the same area of the network are not evident. Nodes of different ethnicities are dispersed across the network. The network may display more ethnic homophily than would be expected by chance, but the lack of separate, ethnically homogenous clusters is telling. Groups co-offended within their own group 45–55 percent of the time, revealing significant levels of co-offending across ethnic lines.

These findings may or may not recur elsewhere. British Columbia is known for ethnically diverse criminal groups (McConnell 2015; McCuish, Bouchard, and Corrado 2015). In network terms, British Columbian gangs may show a lesser tendency for ethnic homophily than do gangs in other regions. This suggests a role for culture in shaping social networks. Patterns found in a region will be a product of availability. Individuals in cosmopolitan regions have access to a wider range of potential accomplices of diverse ethnic backgrounds.

There is accumulating evidence that this may be true elsewhere, as Campana’s (2016b, 2018) results show. Sarnecki (2001) found many more ethnically mixed dyads than expected in Swedish co-offending data. Tenti and Morselli’s (2014) analysis of an investigation of the ‘Ndrangheta suggests that even Italian mafias are more diverse than not, especially when the focus is on the illicit activities they undertake and the social organization of those activities. A single investigation of ‘Ndrangheta involvement in all levels of illegal drug importation and distribution identifies 242 individuals from at least nine different nationalities. Collaboration across nationalities was the norm, not the exception. Nationality was loosely associated with market level; the Italian groups were more likely to be in import and wholesale roles, effectively making them brokers in the network. This brokerage role meant that the Italian groups were collaborating widely with individuals from diverse backgrounds. Their conclusion:

The important point that must be retained after these results is that organized crime cannot be restricted to corporate-like and reputed formal criminal organizations and the actions of illegal market participants cannot be framed as formal organizational boundaries. Rather, organized crime . . . is a matter of criminal opportunity and
necessary collaboration. Illegal market participants are not independent from one another—neither exclusive affiliation to specific criminal groups nor ethnic characterisations emerge as important features in crime. (Tenti and Morselli 2014, p. 39)

The generalizability of these case studies is unclear. There have been few empirical tests of ethnic collaboration in organized crime networks. That many of these studies involved transnational rather than local networks played a role in these findings. Others who have adopted broader, multimarket-level views of networks find greater network diversity, but also more hierarchy, albeit of a rudimentary kind (Varese 2013).

I draw two conclusions from this literature. First, although there is evidence of both diversity and homophily, generalizations around ethnicity per se are unlikely to be productive. Second, the subject should be investigated with network data, and not on the basis of rigid categories that assume fixed entities with simple membership rules.

The degree to which criminal organizations collaborate across ethnic lines can be measured with network data. More precise and potentially meaningful descriptions of the roles of ethnicity in structuring webs of conflicts and alliances across groups can be made if collaborative ties are tracked and followed. Malm, Bichler, and Nash (2011) showed that use of network analyses facilitated description of both the internal dynamics of criminal organizations and the web of connections between organizations at the meso level. This offers a significant development opportunity for the field, especially in understanding conflicts and alliances across organizations (Papachristos 2009; Descormiers and Morselli 2011; Bichler et al. 2019).

D. Crossing the Initial Boundary: Recruitment in Organized Crime

A revolution in place-based criminology happened when street segments replaced neighborhoods as the unit of analysis. Crime is concentrated in only some parts of neighborhoods and may not follow the same trends as in low-crime segments of neighborhoods (Weisburd, Groff, and Yang 2012). It is common, for example, to observe that one street segment is experiencing a crime wave even though crime trends are stable at the neighborhood level.

A network approach can improve understanding of recruitment into organized crime. If a criminal organization is viewed as a fixed entity
(by analogy to “the neighborhood”), almost every recruitment decision can be attributed to the group as a whole or its leader rather than to the subgroup (the “segment”) in which recruitment occurred. For instance, one could say that “Nick was recruited by the organization to run a drug line in the Eastern part of the city.” Nick’s recruitment, however, is likely to have been both simpler and more complicated than this, depending on how it is understood. The simple view is that Nick is Al’s cousin, and Al invited him to join. The complicated view would consider the sequence of events that led to Nick being identified by Al as a potential recruit, the socialization process that acquainted him with other group members, and their opportunities to assess his skill set and trustworthiness; at some point they agreed to make him part of the group. It may, moreover, not have been as simple as Al choosing Nick; Al had also to decide why other potential accomplices were less suitable. Network analyses can situate Nick among the larger pool of potential associates who could have been recruited but were not. With this networked view of recruitment, the mechanisms can be better understood and perhaps better predicted.

Recruitment into organizations like the Sicilian Cosa Nostra or the ‘Ndrangheta would not require a network approach if family lineage was a reliable predictor of who is invited and who is not. But as Varese (2018) has shown after examining recruitment and initiation rituals among the yakuza, the triads, and the Russian mafia, this is not necessarily what happens. The ‘Ndrangheta and, especially, the Sicilian Cosa Nostra have rules favoring the recruitment of family members; other mafias do not. Those who are recruited come from the larger social network around made men. Potential recruits are observed, sometimes for long periods, before they are invited to join. This facilitates screening out police informants, allows testing of trustworthiness and skills, and helps potential recruits learn the organization’s cultural and criminal traditions. Once they become made members, the group becomes their new family. This process occurs among other criminal organizations, such as outlaw motorcycle gangs (Quinn and Forsyth 2011; Blokland and von Lampe 2020). The notion of natal family remains important, but mostly as an analogy and as glue in the social networks assembled as criminal organizations.

A networked view can inform two types of recruitment. The first is the recruitment of individuals invited to join for the first time. The second involves recruitment from within the organization for particular purposes such as a murder conspiracy, a drug-trafficking venture, or to
replace a lost member. Both types are driven by common forces, namely, a combination of criminal human capital (an offender’s skills) and criminal social capital (an offender’s contacts in the organization). Both processes feed on the other (e.g., Coleman 1988); network data are useful in understanding both. For task or role recruitment, it is useful to situate the decision as a search for a suitable accomplice among the larger pool of available associates, using Tremblay’s (1993) model. For initial recruitment, it is useful to think of Nick’s story above, or many other examples in the literature on recruitment. Savona et al. (2017), in a systematic review, describe a culturally entrenched network process that Kleemans and van de Bunt (1999, p. 11) referred to as a snowball effect. They summed up in this way: “Perhaps this snowball effect is the most important principle of the development of criminal associations: people get in touch with criminal associations through their social relations; as they go along their dependency on the resources of other people (such as money, knowledge and contacts) gradually declines; and finally they generate new criminal associations, which subsequently attract people from their social environment again.”

Kleemans and van de Bunt (1999) warned against a view that focuses only on organizations actively recruiting new members; recruitment often occurs organically, as the criminal process unfolds. Often, what we refer to as recruitment is better described as outsiders seeking a role in a particular venture. The extent to which proactive approaches from nonmembers are successful depends on the relative embeddedness of these nonmembers in the organization (are they already connected to one or multiple members?) and the relative importance of the member being approached (does he have influence?). No matter how recruitment unfolds, network mechanisms are at play. The differences in specific mechanisms are a matter of context: who is taking the initiative (the recruiter or the recruited); where is recruitment taking place (the workplace or the neighborhood). Network data accommodate these differences. They are most easily observed in network studies relying on wiretap data: who called whom may reveal the presence of hierarchy in the network, and whether business operations are going according to plan (Morselli 2009).

Most of the evidence on the importance of social networks in recruitment emerges from qualitative social network analysis, in which the role of social ties in recruitment seems ubiquitous. A systematic review of 47 empirical studies of recruitment in organized crime found social ties
to be the most important mechanism of entry among the more than 10 factors considered (Savona et al. 2017). Social network data have a major role to play in understanding the mechanics of recruitment. Yet, very few studies of recruitment were designed around social networks. The main blind spot is a sort of sample-selection bias—sampling on the dependent variable. We examine those who have been chosen but learn little of the larger number of individuals who could have been selected but were not.

Having the network of social relations can help figure that out. The decision to recruit a specific individual is a socially embedded decision. We need simultaneously to consider both the recruiter and the recruit’s networks. Part of why a specific recruit was selected involves not simply his skills or social capital within the organization, but also the importance of the person who is recruiting or vouching for him in the larger network.

Few published studies of recruitment have used social network data to demonstrate the process, but the importance of social ties is fundamental. A prominent example of a networked view of recruitment is Morselli’s (2003) analysis of Sammy Gravano’s rise in the Gambino family. Specific contacts, at different times, allowed Gravano entry into the Colombo and then Gambino families, promotion within the Gambinos, and a lengthy criminal career, even considering major rule transgressions. All turning points were driven by key social contacts that mentored and vouched for him, essential for entry and progression within the families. These social mentors differ from technical mentors in that their main function is to affect their protegés’ involvement in the social networks, and not necessarily to refine their skill sets (Bouchard and Nguyen 2011). Many mentors serve both purposes. Recruitment into criminal organizations goes through networks. This does not mean that criminal competence is irrelevant. Mentors do not take just anybody under wing; they take on protegés who show promise. Social capital creates human (criminal) capital (Coleman 1988), but the reverse is also true.

Morselli’s (2003) analysis reversed the perception that a willingness to use violence to prove loyalty was the main factor in explaining Gravano’s rise in the Gambino family. The network came first, abilities developed, and promotion ensued. Violence came last. Gravano’s network did not grow linearly with each promotional stage. His core network peaked when he became a capo (underboss) and steadily declined until his indictment as Gambino family underboss in 1990. Initially, the recruit is hierarchically
constrained; he relies on the networks of others to climb the hierarchy inside the organization. The recruit crosses the boundaries of the organization based on specific social ties and, if successful, reproduces these network processes at each subsequent promotional stage.

**Networked Decisions: Recruitment for Specific Crimes.** How do organized criminals decide who to include in a murder conspiracy or a drug-trafficking venture? They look around and find the most suitable partners. Progress on this question was made at the conceptual level, even though data, research designs, and methods existed to support existing theories about cooperation among criminals. The intuition that offenders draw co-offenders from a larger pool of associates predates the explosion of social network analysis in criminology. In 1993, Tremblay published an important essay that laid theoretical and research foundations. He argued that the search for co-offenders is purposeful, social, and rational, but involved trade-offs. Not all suitable co-offenders are trustworthy, and not all trustworthy crime partners are suited for the job. Offenders who can best reconcile these dilemmas were hypothesized to achieve better outcomes.

A network approach makes it possible to visualize the extent and nature of the available co-offenders, and model the likelihood a particular co-offender is selected, based on a combination of network position and potential co-offenders’ attributes. Visualization identifies potential candidates, and modeling enhances understanding of selection patterns.

These advantages are not limited to only organized crime studies (McCarty, Hagan, and Cohen 1998). A network approach can improve understanding of the choices and constraints associated with any decision to cooperate. What is distinctive about organized crime is that most of those decisions are made within the context of an organization, meaning that the pool of suitable candidates may be limited. Decisions about recruitment are bounded. Co-offending decisions are freer outside of criminal organizations, but offenders are subject to many of the same kinds of considerations: Who can do this with me, and whom do I trust to execute well and maintain confidences if caught by the police?

McCuish, Bouchard, and Corrado (2015) studied recruitment decisions in organizing three murders. The group, initially a youth gang, grew into a criminal organization during the 10 years they were followed. Access to official co-offending data during that period was available, which provided complete networks related to all three murders (all led to convictions), but those data could not track social and criminal ties...
not known to the police. For most crimes, gang members co-offended with people in and outside the gang, but for murder conspiracies, all participants were recruited from the gang leader’s inner circle of members. Members were more trustworthy than outsiders; the higher the stakes, the more likely members were to be selected.

Collaborations in organized crime ventures are often based on trust, making some recruitment and co-offending decisions less than optimal (Tremblay 1993). Network data highlight constraints faced by organized criminals and demonstrate individual differences in access to social opportunity structures that characterize organized crime (Morselli 2003; Kleemans and De Poot 2008; Bouchard and Nguyen 2011).

III. Dangers in Interpreting Network Data

Network data are vulnerable to the biases that affect other criminal justice data: incompleteness, recall bias, and overemphasis on some groups at the expense of others (Campana 2016a). Campana and Varese (2012), focusing on wiretap data, provide the most comprehensive examination of limitations of illicit network data.

In this section, I discuss limitations of three kinds: overinterpretation, overcomplexification, and oversimplification. Many of these dangers result from lack of contextual data. Network data should normally contain more context information than is possible in traditional quantitative studies.

A. Overinterpretation

When network data are the only or main source of information, it is easy to see more patterns than exist. There is, for example, always a risk of imputing too much intentionality and purpose to observed network patterns. A person may have many connections to others in a criminal network, and link otherwise disconnected individuals, but not take advantage of co-offending possibilities or even recognize them. This may be more common than we know. Researchers seldom ask offenders to describe their self-perceived network position, or their strategies to take advantage of their social networks. Even if individuals are unaware of their network positions and its potential benefits, they are in a position to benefit from their network positions. The potential benefits exist.
Whether they are recognized is another matter entirely. Social capital consists of the ability to use social connections (Lin, Cook, and Burt 2001), not their number or quality. A person could have comparatively few connections but use them exceptionally effectively. Network scholars need to do more to demonstrate that central players are aware of their connections and use them strategically.

A related overinterpretation error is more common: interpreting the whole network while forgetting it was built for particular reasons. The origins of the network always matter, for the same reason they matter in snowball sampling: network composition will be shaped by the seeds from which it grew. The more seeds and the greater their diversity, the more likely we are to understand the characteristics of the population making up the network. Conceptualizing network construction as a sampling process acknowledges that researchers make choices, often arbitrary ones, on whom to include in the network; those choices have implications for interpreting the results. Overinterpretation occurs when scholars interpret the network positions of seeds and nonseeds on the same level. Valid interpretations should always be made on two separate levels—seeds versus nonseeds (e.g., “Among seeds, the most central is . . . Among nonseeds (i.e., alters), someone who emerges as potentially important is . . .”; Varese 2013; Hashimi and Bouchard 2017).

B. Overcomplexification

Network scholars can become too enthusiastic. Networks can grow almost infinitely. A follow-the-links approach has, in theory, no objective end. In practice, letting networks grow too far away from their seeds confounds analyses. To the extent that the network starting point was well chosen (e.g., a mafia leader, members of a Hells Angels chapter), extending it three or four steps from the original seeds can significantly change its nature. An analysis can begin from an original seed and be extended to include the seed’s network, the connections of the seed’s connections, and their third-order connections. By the end of the process, the network around the seed could contain 100 or more individuals. The starting point remains relevant; the 100 are known because they are within three steps of the seed. However, the network is no more the seed’s than it is the network of any one of the 100 others. Indirect connections diffuse through networks and influence criminal behavior (Papachristos 2011), but interpretations must reflect these complexities.
C. Oversimplification

Oversimplification often results from missing data. All researchers recognize the need to manage missing data problems. With network data, a missing node or link may fundamentally distort characterization of the network (Morselli 2009; Campana and Varese 2012), especially if the network is small. Interpretive errors concerning large networks missing, say, 10 percent of nodes, are less likely than concerning smaller networks in which the 10 percent missing data may be crucial (Burcher and Whelan 2015).

In network analyses, data missing from law enforcement databases can be crucial. Researchers can see, and code for, data concerning people seen by the police, or whom the police think relevant (wives or girlfriends may sometimes be excluded). People who escape police attention do not appear. Some individuals identified in police data are likely not to be central, and are thus unlikely to be picked up in the network analyses. How does someone become visible and central in police data? Typically, by being arrested more often than others who might have been. Those arrested often are not the people at the center of events underlying major crime investigations.

Those issues can be addressed. Multivariate analyses can control for offenders’ relative network exposure, net of other important patterns being investigated. The use of data from multiple years often compensates for the effect of including data for some offenders from an atypical year, for instance, years in which they were the targets of major police investigations. Use of multiple data sources can compensate for limitations of any one source. The focus in arrest data on the event and visible co-offending can be offset by adding surveillance data (Rostami and Mondani 2015), if available, or police contact data (Hashimi and Bouchard 2017; Ouellet, Bouchard, and Charette 2019). Criminals, even masterminds, do not fully avoid having police records, even if they are never convicted.

IV. The Future of Research on Networks and Collaboration in Organized Crime

Network research on organized crime is constantly evolving. Myriad research questions need better answers. I discuss four: how and when boundaries form, variations in cultures of collaborations, age boundaries, geographical boundaries.
A. How and When Boundaries Form

Network data can capture dynamics that exist within criminal organizations, changes in relationships between stable members, and changes in the relative importance of peripheral members who come and go. Network researchers are less interested in changes in the number of members than in the structure of the organization. For example, is it becoming more centralized around a few leaders, as may have been intended during a retrenchment phase, or does the social network of collaborations among members tell a different story?

This approach allows us a chance to draw from network theory to make predictions about survival. Ouellet, Bouchard, and Charette’s (2019) study of gang persistence showed that forming alliances outside the organization was key for the survival of the relatively small groups that make up the bulk of organized crime. For large groups, the opposite was true: the more outside alliances, the lower the likelihood of survival. Network descriptions of different criminal organizations may thus facilitate understanding of how they are likely to evolve over time, including their capacity to adapt to disruptions caused by law enforcement (Morselli 2009; Bright, Koskinen, and Malm 2018) and conflicts with other groups (Papachristos 2009; Bichler et al. 2019). Study of illicit networks is largely descriptive and cross-sectional. Work on longitudinal networks has mostly been conducted in the classrooms of hundreds of American high schools. With a few notable exceptions (e.g., Bright, Koskinen, and Malm 2018), the resulting models have rarely been applied to organized crime networks (Ouellet and Hashimi 2019). The opportunity to look into how and when boundaries form is likely to drive the research agendas of many crime and network scholars in the near future.

B. The Emergence of Cultures of Cooperation

Collaboration and group boundaries need fuller study and explanation using network data and methods. That organized criminals collaborate is not mysterious. Christakis’s Blueprint (2019) shows that collaboration emerges in any society as part of the fabric of human life. However, variations exist in the forms collaboration takes. Some groups form highly centralized networks, with connections passing through only a few individuals, like the core-periphery structures discussed above. Others are more egalitarian; network members have relatively similar numbers of ties to others. Christakis argues that variations are shaped by a combination of the environments in which they are embedded and the cultures
of cooperation developed among network members. Consider, for example, the 19 hijackers involved in the 9/11 terrorist plot; their network was long and sparse, with few strong ties within or between different hijackings (Krebs 2002). The stakes were high, and the time required was substantial, making it necessary to keep the conspiracy going for a long time without being detected (Morselli, Giguere, and Petit 2007). This favored a snake-shaped network in which failure of one part of the network would be unlikely to cascade through the rest. Each individual member knew little about the whereabouts of others. The efficiency-security trade-off favored security. Security concerns are associated with sparse networks, efficiency with dense ones (Morselli, Giguere, and Petit 2007).

Criminal organizations have agency in creating cultures that favor more effective collaboration. A cultural environment favoring collaboration is associated with growth and survival of criminal organizations. Organizations that foster environments in which cheating and defections are common are more likely to fail. Just as in the legitimate world, differences in organizations’ capacity to establish a culture of cooperation are associated with tangible outcomes, such as longer survival, or high collective achievement (Tremblay, Bouchard, and Petit 2009; Sergi 2016). Ouellet, Bouchard, and Charette (2019) showed that small groups benefit from recruitment; the competency of recruitment decisions, however, is important. Growing in the right way may be crucial to survival of smaller groups.

The preceding observations are hypotheses. There have been few or no empirical demonstrations of the interplay of culture and collaboration in organized crime. It would be challenging to adapt Christakis’s (2019) online experiments to real-life organized crime. A way forward would involve combinations of qualitative data on cultures and subcultures with network data on interactions within the subculture (for a brilliant example of concerning gangs, see Tremblay et al. 2016).

C. Age Boundaries

A focus on connections between individuals as a main unit of analysis is bound to pay attention to aspects of organized crime collaborations that are otherwise easily overlooked. Age differences between individuals are one indicator that would benefit from greater attention. Age difference is an indicator of mentorship, an indicator of longer, more successful criminal careers (Morselli, Tremblay, and McCarthy 2006). Scholars
interested in criminal trajectories, including whether juvenile delinquency is likely to lead to adult criminality (e.g., Savona et al. 2017; Blokland et al. 2019), should pay attention to relationships between offenders of significantly different ages. Adolescents who interact only with others of the same age are much more likely to desist from crime when they become adults. Having role models, in crime or otherwise, helps frame career paths.

At the organization level, groups that maintain ties to younger people are more likely to survive (Ouellet et al. 2019). The organizational model of the Hells Angels and of other outlaw biker clubs includes establishment of puppet clubs from which future members are recruited (Morselli 2009; Quinn and Forsyth 2011). Similar mentoring functions have been observed in the larger networks of mafia families; they ensure that recruits are properly vetted and that they learn the rules of behavior inside the family (Varese 2018). These cultural and knowledge transfers are inherently social in nature (Sutherland 1937) and best approached with network data. A potential benefit of this approach, at the meso level, is improved understanding of the evolution and demise of criminal organizations. Organizations with healthy stables of potential recruits and a tradition of promotion and cooperation are more likely to survive.

D. Crossing Geographic Boundaries

Network studies of transnational organized crime are not common. Campana (2016b, 2018) constructed transnational networks from major investigative files in a number of countries. Access to files documenting collaborative activities of offenders from multiple countries is often available only in the country whose law enforcement agencies have jurisdiction (e.g., Varese 2013; Tenti and Morselli 2014). These types of studies are important because offenders coordinating cross-border trafficking are often role models, sources of inspiration to other criminals who look up to them (Tremblay and Morselli 2000). They are few in number and hard to detect (Bouchard and Ouellet 2011) and potentially make the most money from crime (Reuter and Haaga 1989; Desroches 2005; Bouchard and Ouellet 2011). Their influence needs to be studied.

This small body of research sets the stage for deeper looks into networks that cross geographical boundaries. The interplay of local connections, and connections that span multiple countries, is poorly understood. Few members of transnational networks are aware of activities and connections beyond the local level. Future research needs to target the
drivers of those differences, and whether these networks’ transnational nature concerns only select individuals in coordination roles. The implication would be that there is perhaps no transnational organized crime per se; only a few select individuals who broker deals across multiple countries.

V. Conclusion

Morselli (2003) observed that much of the traditional literature on mafia families revolved around networks. From Ianni and Reuss-Ianni’s (1972) patron-client relationships to Haller’s (1990) fraternity of criminal entrepreneurs, organized crime scholars had difficulty describing the functioning of criminal organizations without emphasizing their social networks. Their frameworks fit within the family of network approaches to crime; they can be enriched by collecting network data. Doing so reveals the mechanisms at play in collaboration among organized criminals. It permits boundaries to be drawn: who is part of the organization and who is not; who is recruited and by whom; and how the organization evolves, reproduces, and survives. Network data clarify the context, for example, of recruitment decisions. Network data are mainly, but not solely, about mapping relations. It is also about understanding why those relations were formed.

How else can alliances across criminal organizations be described accurately? It is indeed challenging to describe the interconnections among cells in a drug distribution chain without referring to networks, or using network terms. The terms “cell,” “connection,” and even “chain” are the building blocks and foundation of network theory. The leap from thinking of organized crime in terms of network analogies, and consciously applying network data and methods, is not a large one.

Network data by themselves are not enough. A network approach is sometimes possible only when other sources of data and theory are available. Economic approaches are needed to understand market forces that explain involvement in one market but not another. Situational approaches make sense of the decision making involved in establishing an importation route. Subcultural theory aids understanding of the origins and effects of norms on behavior (Kleemans 2014). This volume of Crime and Justice is illustrative. Many of the essays discuss similar subjects but use different
perspectives. Most refer to work of others that is informed by different perspectives.

I did not discuss other promising areas of research on organized crime that could benefit from network approaches. They can also be used, for instance, to gain insights into conflicts among criminal organizations. Here, the analysis operates in reverse; rather than seek better understanding of collaboration, the aim is to understand noncollaboration—antagonistic relations among organized criminals. The theoretical foundation is the same; conflicts are inherently social acts. Each violent act in a conflict has a history, symbolic meanings, and, because conflicts involve multiple incidents, implications for future incidents. The retaliatory nature of conflicts has an indirect consequence of expanding the social networks in which groups are embedded. A network approach can help understand patterns of conflict that are likely to recur because they are integrated in the identities of the protagonists (Papachristos 2009). Studying alliances and conflicts together makes possible informed predictions about who will win the conflict.

I also did not discuss practical implications of adopting a network approach; they are a selling point for law enforcement agencies contemplating collaborations with academics. Understandably, practitioners have been attracted by the prospect that social network analysis may facilitate the disruption of criminal groups (Bichler and Malm 2015). In principle, those developments are positive; couching target selection decisions for violence reduction in network data is usually an improvement over traditional approaches that often use no systematic data at all.

In practice, policy recommendations stemming from network analyses are only as good as the data used to generate them. Biased data produce biased recommendations. Traditional practices, however, may produce even more harms because of the same biases. Network methods can accentuate biases existing in the data. They can also be used to detect biases. Incorporation of novel methods in law enforcement practice should be accompanied by a concern for transparency, a willingness to independently evaluate performance, and an aim to reduce inequality.

Most of the organized crime literature takes networks for granted. Little is known about why particular individuals rise to their network positions, or what forces cause networks to take one form and not another. Network structures emerge from the interplay of social forces that operate in all social groups. They are at the heart of collaboration in organized crime.
REFERENCES


