RESEARCH ARTICLE

To racketeer among friends: spatial features of criminal collaboration in the American Mafia

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ABSTRACT
The American Mafia is a network of criminals engaged in drug trafficking, violence and other illegal activities. Here, we analyze a historical spatial social network (SSN) of 680 Mafia members found in a 1960 investigatory dossier compiled by the U.S. Federal Bureau of Narcotics. The dossier includes connections between members who were 'known criminal associates' and members are geolocated to a known home address across 15 major U.S. cities.

Under an overarching narrative of identifying the network's proclivities toward security (dispersion) or efficiency (ease of coordination), we pose four research questions related to criminal organizations, power and coordination strategies. We measure how the Mafia network is distributed as a portfolio of nearby and distant ties, the locations of high-degree network members, the role of spatial and social clusters, and the overall efficiency of the network.

The methods used here differ from former methods that analyze the point pattern locations of individuals and the social network of individuals separately. The research techniques used here contribute to the body of non-planar network analysis methods in GIScience and can be generalized to other types of spatially-embedded social networks.

KEYWORDS
Organized crime; spatial social networks; Italian-American Mafia; Midcentury U.S. History; GIS

1. Introduction

1.1. *The American Mafia*

The American Mafia is a network of loosely-affiliated criminal groups responsible for violent and illegal activities over the course of many decades. Inspired by similar organizations operating in southern Italy, the American Mafia emerged in the U.S. in the early 20th century (Abadinsky 1981). In addition to causing widespread violence and disorder, one 1960s U.S. Department of Justice estimate suggested that Mafia-affiliated groups grossed about 40 billion USD annually (Maas 1969) in illegal or untaxed industries.

The Mafia did not exist to carry out any single attack, criminal conspiracy, or collective action but thrived in a diverse range of (typically illegal) business activities. Criminal collaboration in the Mafia included ties within and across *families* (Della-Posta 2017), the unit of organization that drove the Mafia. Family organizations contained both formal and informal hierarchies in which some members held higher-status positions than others (Gambetta 1993). Members gained benefits and "protection" in their criminal activities by belonging to a family, and were expected to demonstrate loyalty to the family in return.

In the 1950s and 1960s, during the height of their operations, the Mafia became increasingly subject to major federal investigations (e.g. U.S. Senate 1951, 1963, 1988, Bureau of Narcotics 2007), leading to high-profile trials and arrests, as well as greater knowledge of their criminal activities. These investigations furnished a wealth of information on the background and activities of members, some of which has only recently been made public. The Mafia has continued to fascinate the general public, as evidenced in popular cultural artifacts like *The Godfather* and *Goodfellas*. Many of the families included in this study continue to operate in some form today, attesting to the Mafia's adaptability in changing social conditions (Zimmerman and Forrester 2020).

1.2. *The efficiency-security tradeoff and geographic space*

Successful Mafia families formed alliances with one another across distances and across families, but also operated locally with extensive networks of collaboration within families. This dual structure put tension between business efficiency and covert security, as captured by the concept of the *efficiency-security tradeoff* (Morselli *et al.* 2007, DellaPosta 2017). *Efficient* criminal networks ensure that their members are well-connected so that resources and information can move easily; however, *secure* criminal networks feature sparse, decentralized arrangements that prevent the discovery of one member from implicating the rest of the network.

Extending the *efficiency-security tradeoff* (Morselli *et al.* 2007) to its geographic dimensions, Mafia members theoretically benefit from having both nearby and distributed ties. Nearby families and associates could easily coordinate collaborative criminal behavior and share information, especially since mafiosi preferred to share information in person rather than risk wiretapped phone conversations. Mafia industries or 'rackets' cornered the neighborhoods and kept out competitors (Gambetta 1993). Nearness let members monitor and exert social control over criminal colleagues, since mafiosi could not resort to conventional legal or institutional mechanisms to mediate disputes. Clustering also allowed for a monopolistic presence in a neighborhood and control of turf by powerful groups. Poorer neighborhoods were especially good targets for racketeering, and neighborhoods with many Italian immigrants were often emphasized as a key locus of coordination for urban racketeers (e.g. Bell 1953).

However, geographical dispersion was attractive because it meant increased security and ability to evade law enforcement, and could reduce the risk of implicating fellow associates. Also, distributing trusted family agents across cities allowed access to various trade markets and customer/victim bases. This was especially imperative for the lucrative narcotics trade which spanned across multiple cities and international borders (U.S. Senate 1963). Similarly, the import and export of legal goods (such as cheese and olive oil from Italy), required coordination across space to achieve wide distribution of products.

1.3. *Research questions*

Within this context, we seek to measure the extent to which the Mafia strategically leaned toward security or efficiency in their residential distribution, and to look for evidence of top-down or bottom-up coordinated efforts. Here, we use a detailed data set of 680 individuals (affiliated with 24 Mafia families operating around the year 1960, when the data set was produced) and their connections to one another. Individuals are geolocated to their home address, forming a spatial network across large U.S. cities. The network was collected by the U.S. Federal Bureau of Narcotics (predecessor to the modern-day Drug Enforcement Administration). We expect criminal locations to have facilitated efficient communication and resource movement while avoiding detection. Our research questions examine families, nodes (individuals), edges (ties of criminal collaboration) and network structure, respectively, and are as follows:

Q1: Do families tend to live in clusters or distributed locations? Given the risks and opportunities of distributing families across geographic space, we show how families balanced efficiency and security concerns, and examine whether all families exhibited similar strategies in distributing their members.

Q2: Do criminal associates tend to live near one another, and were nearby members likely to be associates? While Q1 focuses on the location of families, Q2 measures the extent to which ties tended to concentrate or disperse over space. We also examine how inter-city ties linked families into an efficient and well-connected national network.

Q3: Are high-degree members found near their family centers, high income areas or near strategic physical features? Powerful members may locate at the geographic center of the family network to be accessible to collaborators, and to monitor activities. They also may live in high-income areas, and near strategic physical features. We evaluate this question for New York City-based residents, where many key high-degree individuals lived.

Q4: Does the network exhibit efficiency in geographic space? Covert organizations create centralized structures to ease communication and coordination, while also remaining undetected through sparse and decentralized communication. While the other research questions all speak to elements of efficiency and security, with Q4 we present overall metrics summarizing the extent to which the entire network is clustered or distributed.

This work is part of a growing body of spatial social network (SSN) analysis. Despite its descriptive nature, this analysis contributes to the GIScience literature by providing new metrics and serving as a case study for newly-established SSN methods. This approach differs from typical GIS assessments of crime data events, which tend to analyze disconnected events at the point level or crime statistics at the aggregate areal unit level. The SSN analysis research framework reveals information about the system's distribution of power, information flow and coordination strategies in geographic space. In the following sections, we review literature, describe our dataset and analytical methods, report results and discuss the findings in the context of our research questions.

2. Literature Review

The Mafia is an inherently local and place-based institution; the opportunities for profitable Mafia crime emerge out of local institutional conditions typified by a lack of government control and widespread distrust among citizens (Gambetta 1993). Paradoxically, widespread mistrust is simultaneously the problem that the mafioso steps in to solve (i.e. by providing private protection in areas lacking rigorous public controls) *and* the state of affairs that the Mafia must maintain (i.e. by injecting further violence and disorder) to keep up demand for its services (*ibid.*). Local conditions gave rise to both the supply of criminals and demand for services. In this section, we provide background knowledge on the American Mafia, describe how organized crime is intertwined with geography, and review an overarching strategy for optimizing power in geographic space based on the notion of efficiency-security tradeoffs.

2.1. *The Mafia organization*

Mafia organizations are built on a foundation of trusted network ties among their members (Gambetta 1993) and are centered around 'families', i.e. members arranged in an organizational hierarchy led by a boss (Gambetta 1993, Abadinsky 1983, Maas 1969, Paoli 2003, Cressey 1969, Catino 2019, Reuter 1983). A family is an elective grouping of individuals, and does not necessarily indicate actual kin ties (although some members are kin through blood or marriage). Network ties *within* as opposed to *across* families have been found to be 56 percent greater than expected by chance, and even for families co-located in New York City, within-family ties still occurred 33 percent more than expected by chance (DellaPosta 2017). While families largely functioned independently from one another, they were nonetheless linked through network ties and ongoing collaborations, and held periodic meetings to coordinate their efforts (Gambetta 1993, Abadinsky 1983, Maas 1969). The most memorable such meeting occurred in 1957 in Apalachin, N.Y.; law enforcement discovered and raided the meeting, arresting more than 50 high-ranking mafiosi from locales as diverse as Denver, Tampa, and Los Angeles (Bureau of Narcotics 2007).

While Mafia families borrowed legacies and traditions from similar groups in southern Italy (especially the Sicilian *Cosa Nostra*), they were organizationally distinct. As Gambetta (1993) quotes from one American mafioso: 'If [someone] lives [in Italy]...he can't be one of us' (p. 117). In New York City, Italian-American racketeers initially divided along regional lines based on area of Italian ancestry (especially Neapolitan vs. Sicilian origin). By the middle of the 20th century, Italian-American Mafia families had also emerged in most other major American cities, and NYC was defined by a five-family system which would persist for decades.

Mafiosi were career criminals and the families were long-running operations, many of which still exist today. Families acted as organizational umbrellas for coordinating collaborative enterprises, forming network ties, and mediating disputes between members (Gambetta 1993). Their activities resemble ongoing processes, rather than fixed criminal events. Mafia families were united by a shared set of rules, such as the requirement that a 'made man' (full member) be of full-blooded Italian ancestry (Maas 1969). In total, the American Mafia was said to be comprised of between 20 and 30 distinct criminal organizations or families at different points in time over the last century (Maas 1969); in the data set for this study, we identify 24 families.

Individual members operated with a high degree of autonomy, seeking profitable, entrepreneurial opportunities in both legal and illegal industries while collaborating with partners both inside and outside of the family (Reuter 1983). The mafioso's personal network of criminal associates was his most valued resource (Abadinsky 1983). Joining a family meant gaining access to profitable rackets and business opportunities. Accordingly, individual members sought good standing within one's family by following rules set by higher-ups and sharing profits with *capos* (captains or lieutenants in the organizational hierarchy) and bosses (Maas 1969).

2.2. *Organized crime and geography*

Organized crime is inextricably connected to space, from the movement of offenders, to the location of spaces that promote or deter crime, to physical or social boundaries (Hipp and Williams 2020). The relationship between space and organized crime has been studied in several disciplines, including geography (Hall 2012, Dolliver *et al.* 2018), sociology (Moro and Villa 2016, Papachristos *et al.* 2013, McLean *et al.* 2018), criminology (Hipp and Williams 2020, Tita and Radil 2011, Tita and Greenbaum 2009), and economics (DeAngelo 2012, Glaeser *et al.* 1996). Criminal violence leads to greater geographic and social isolation as well as stress on well-being, and heightened criminal activity can devalue geographic space (Graif *et al.* 2017).

Geographic space can be viewed as a stage upon which crime takes place. This relationship most frequently takes the form of 'turf,' i.e. a bounded space to which an organization lays claim (Brantingham *et al.* 2012, Papachristos *et al.* 2013). Criminal space is continually redrawn by the interactions within and across territory (Tita and Greenbaum 2009). Organized crime groups use space depending upon its viability for enterprise. For example, Moro and Villa (2016) found that organized crime in Italy's Lombardy region was propelled by economic sectors with low barriers to entry, such as construction and transportation.

At the street level, immediate surroundings are used to perpetuate crime. Criminals gather clues from the surrounding environment to determine the best ways to carry out activities, and tend to select targets near areas with which they are most familiar (called 'awareness spaces') (Brantingham and Brantingham 2017). Criminals' relationship to territory can also change over time and space as the result of competition between organizations over business (Brantingham *et al.* 2012) and shifts in type of criminal (and non-criminal) activity (McLean *et al.* 2018). The particular configuration of the built environment (He *et al.* 2020, Summers and Caballero 2017) is also important. Radil *et al.* (2010) used a SSN model to show that inter-gang crime in the Hollenbeck area of Los Angeles correlates with Euclidean distance between gang territory and the built environment (roads, bridges, etc.).

Distant ties and nearby ties have different benefits in the context of organized crime. Close proximity leads to greater interaction (Papachristos *et al.* 2013, Giommoni *et al.* 2016). As a result, crime tends to spatially cluster, not necessarily due to the proximal amenities, but due to spatially-embedded social interactions (Tita and Radil 2011, Glaeser *et al.* 1996, Bastomski *et al.* 2017). Dense social networks of co-offenders appear to be related to more criminal activity in neighborhoods (Bastomski *et al.* 2017). Distant ties, however, allow for goods to travel along social infrastructure (i.e. trusted relationships at origins and destinations). Drug trafficking often follows the same type of geographic routes that legal trade follows in order to take advantage of existing logistical infrastructure and operations (Giommoni *et al.* 2016). Distant social ties also help criminal activity to persist across borders (Giommoni *et al.* 2016), and these operations necessitate the need for distant ties. Today, criminal ties are now also sustained over virtual cyberspace (Dolliver *et al.* 2018).

Different types of crimes exhibit different spatio-temporal patterns; for example, assaults are more likely to occur near other assaults within short time periods (Grubesic and Mack 2008). Moreover, crime occurs in predictable places and times, and as such, time-geographies can be policed or transformed in order to prevent unwanted activity. For example, Corcoran *et al.* (2019) find that in Queensland, Australia, property theft, property damage, and drug crimes are most likely to occur in commercial zones at night. In their study of distance from home to the site of homicide victims and perpetrators, Groff and McEwen (2005) show that in gang-related homicides, both parties are more likely to be farther from their homes than is the case for other types of homicides. Lastly, in Beijing, co-offending criminals organize into groups from the same hometown or neighborhood, and outsiders tend to connect with to multiple co-offending groups (Chen and Lu 2018).

2.3. *Efficiency-security tradeoff*

Criminal organizations and their members navigate a key tension between *efficiency* and *security* (Morselli *et al.* 2007). A network that balances this tradeoff seeks to maximize the efficiency of information flow, while keeping ties clandestine and avoiding detection. The most efficient network (e.g. a clique) is convenient but vulnerable, as one person who gets arrested can implicate many others. The most secure network might be a linear chain-like structure, where no one person can implicate the entire organization—but this network does not disseminate information quickly.

Covert organizations vary in the way that they navigate the efficiency-security tradeoff. Terrorist networks, which often exist for the time-delimited purpose of carrying out a particular attack, tend to develop sparse and decentralized chain-like structures that maximize security by minimizing any one member's ability to implicate others and reveal the conspiracy (Krebs 2002; though McMillan *et al.* 2020 find that terrorist networks become increasingly centralized as the time of attack approaches). Such decentralized structures are less likely among Mafia families, which seek to perpetuate themselves and their control over industries without a specific time horizon. Operating more like businesses in other realms, Mafia families should tend to form networks that favor efficiency and centralization over security and decentralization. Using the same data as the present study, DellaPosta (2017) found that Mafia families form internally dense and cohesive networks that connect across families to produce a 'small-world' structure (Watts and Strogatz 1998) with high reachability.

While we are not aware of previous research that examines the efficiency-security tradeoff in the context of geographic space, the geographic tradeoff can be conceptualized in terms of two extremes. At one extreme, individuals would form a chain across cities; and the other extreme would be if all individuals clustered, spatially and socially, at the same location. We expect the Mafia network to form a hybrid between these extremes.

3. Data Description and Methods

3.1. *Data description*

Our data are drawn from a dossier compiled in 1960 by the United States' Federal Bureau of Narcotics to bring together knowledge from disparate previous investigations of individual criminals and criminal groups. The dossier contains one-page profiles of individual mafiosi (i.e. Mafia members) and their demographic background, residential address, criminal background, and a list of known 'criminal associates' (Figure 1). Data from this dossier has been used to examine network clustering tendencies and individual-level correlates of centrality (DellaPosta 2017, Mastrobuoni 2015, Mastrobuoni and Patacchini 2012). The dossier was originally produced only for internal use by government officials; however, it was more recently declassified and published for the general public in 2007 (Bureau of Narcotics 2007).

Network edges are created by linking 'criminal associates' listed in each profile. While these nominations are not always reciprocated, we treat criminal association as unweighted and undirected. While the criminal profiles sometimes referenced associates outside the dossier, we restrict analysis to mafiosi with criminal profiles. Nodes (i.e. members) are assigned to a family based on the dossier or from organizational charts gathered from Congressional reports (U.S. Senate 1963). When evidence is lacking, a label propagation algorithm (Raghavan *et al.* 2007) was used to assign mafiosi to a primary family (see DellaPosta 2017).

The Bureau of Narcotics data set has benefits and limitations. While communication networks constructed from "wiretaps" often miss high-ranking criminals (who delegate communication tasks to lower-ranking criminals; see Agreste *et al.* 2016), our data (not based on direct communication records) capture these individuals. Ties in the dossier reflect investigators' overall perceptions of who was connected to whom (i.e. a "reputational" approach; see Campana and Varese 2020). However, it remains possible that investigators could have wrongly attributed certain ties due to imperfect information and missed others; further, members who managed to elude investigation would not be present in the data.

3.1.1. Network properties

The original network derived from the dossier included 808 members; 717 members have addresses and 707 can be assigned a primary affiliation with one of 24 Mafia families. 692 members have both a family affiliation and an address and 680 have at least one tie, and thus are considered as part of the connected network. The data includes men (and one woman) ranging in age 18-80. Nearly half of the members were born in Italy (typically Sicily and southern Italy), while the remainder were largely born in the U.S. of Italian ancestry. The network is connected by 2,699 unweighted, undirected edges. The network's diameter is 10 (Figure 3) and the average path length is 3.887. The network has a clustering coefficient of 0.31 and 135 members have a clustering coefficient of zero. Individuals' degree ranges from 1-77 (ave. 7.033, std. 6.45). Each member belongs to one of 24 families (Table 1) whose sizes, mean degree and expanse over number of cities (i.e. metropolitan statistical area) varies.

3.1.2. Geographic network properties

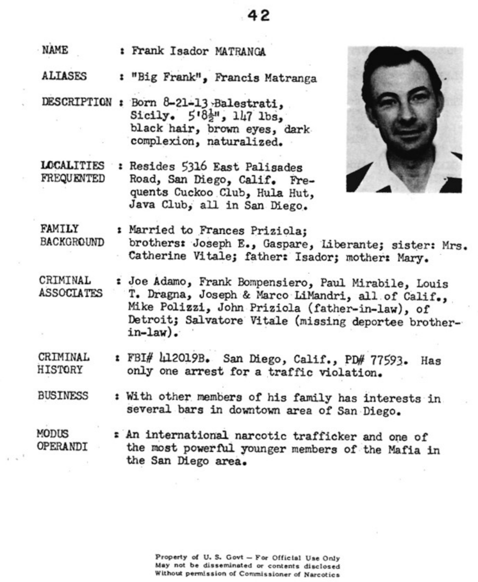
The following states have at least five members of the network: New York (n = 326), New Jersey (58), California (50), Illinois (41), Michigan (41), Florida (39), Missouri (29), Pennsylvania (24), Louisiana (17), Ohio (16), Colorado (9), Massachusetts (7), Texas (7) and Connecticut (5) (Figure 2). They live in 77 counties, and concurrently in 43 metropolitan areas. All members fall within a metropolitan area (given 2010 distinctions, which are likely to be larger than the functional urban areas in 1960s), except for one member of the Colorado family who lived about 100 kilometers south of Pueblo, Colorado. The average edge distance is 288 km and standard deviation is 744 km.

3.1.3. New York City

New York City (NYC) is both a geographical and organizational center of this network, and home to the well-known "five families": the Genovese, Lucchese, Gambino, Profaci and Bonanno families, who together comprise 46% of the network (Table 1). Three members from the nearby Elizabeth (NJ) family and one member each from the Buffalo

Table 1. Critical statistics by family for the 680-member network.

Family	Members	Degree Range	Mean Degree	Num. Cities
Genovese	149	1-46	7.6	7
Lucchese	124	1-77	7.7	6
Gambino	67	1-28	6.2	5
Detroit	44	1-25	8.4	5
Chicago	39	1-22	4.4	3
Los Angeles	30	3-21	9.4	3
Profaci	24	1-39	6.2	1
Kansas City	19	1-15	8.7	2
New Orleans	19	1-13	5.3	4
Pittston (PA)	19	2-17	7.2	3
Bonanno	18	3-26	7.7	3
Buffalo	18	2-17	8.1	4
Cleveland	17	1-11	5.1	3
Florida	16	1-17	6.1	2
Philadelphia	13	2-11	7.1	2
San Francisco	13	1-10	3.3	5
St Louis	11	2-17	7.3	1
Colorado	9	4-11	6.8	2
New England	9	3-8	5.6	3
Dallas	7	3-6	4.9	2
Pittsburgh	6	5-11	6.8	1
Omaha	4	2-4	3.3	1
Elizabeth (NJ)	3	3-6	4.3	1
Springfield (IL)	2	1-2	1.5	1



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NAME : Frank Isador MATRANGA

ALIASES : "Big Frank", Francis Matranga

DESCRIPTION : Born 8-21-13 Balestrati, Sicily. 5'8½", 147 lbs, black hair, brown eyes, dark complexion, naturalized.

LOCALITIES FREQUENTED : Resides 5316 East Palisades Road, San Diego, Calif. Frequents Cuckoo Club, Hula Hut, Java Club, all in San Diego.

FAMILY BACKGROUND : Married to Frances Priziola; brothers: Joseph E., Gaspare, Liberante; sister: Mrs. Catherine Vitale; father: Isador; mother: Mary.

CRIMINAL ASSOCIATES : Joe Adamo, Frank Bompensiero, Paul Mirabile, Louis T. Dragna, Joseph & Marco LiMandri, all of Calif., Mike Polizzi, John Priziola (father-in-law), of Detroit; Salvatore Vitale (missing deportee brother-in-law).

CRIMINAL HISTORY : FBI# 412019B. San Diego, Calif., PD# 77593. Has only one arrest for a traffic violation.

BUSINESS : With other members of his family has interests in several bars in downtown area of San Diego.

MODUS OPERANDI : An international narcotic trafficker and one of the most powerful younger members of the Mafia in the San Diego area.

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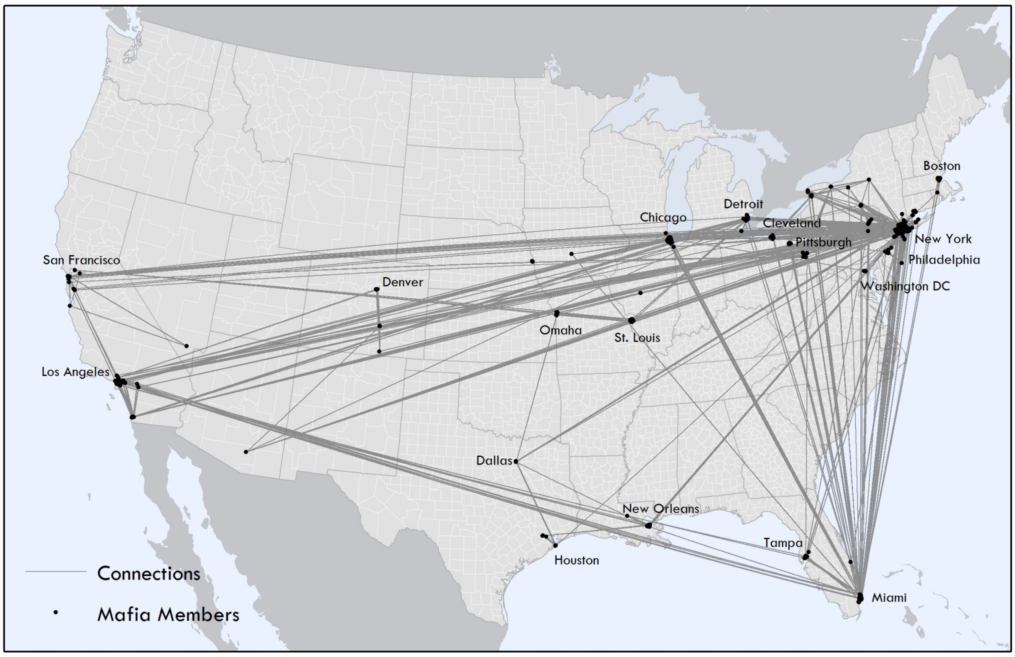
Figure 1. Example entry from dossier compiled in 1960 by the Federal Bureau of Narcotics. Relevant information used in this study includes address (for geolocation) and criminal associates (for social network formation).



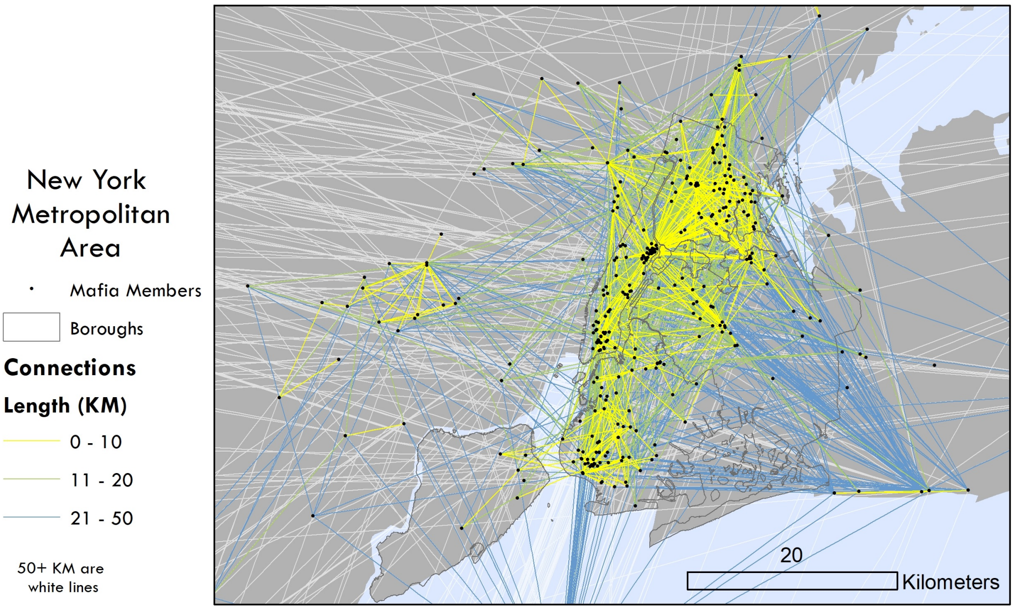
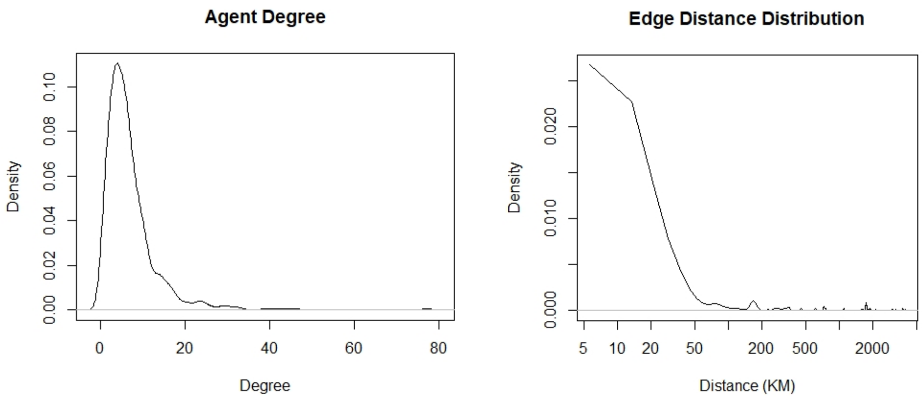


Figure 2. Top: Mafia ties were distributed across the country with notable links to Miami, FL and Los Angeles, CA. Bottom: Ties were concentrated in New York City forming clusters in Manhattan and Brooklyn.



(a) (b)

Figure 3. (a) Degree distribution and (b) edge distance distribution of Mafia members.

(k=4), Detroit (k=3) and New Orleans (k=6) families are also based in NYC.

The city is unique in having several local families, as all other cities are either dominated by a single local family or designated as 'open' territories (e.g. Miami, Las Vegas). Of the families, Los Angeles members have the highest average degree and the Genovese family has members across the most MSAs. Thirty-six members of NYC families live outside the city, and while these members tend to live without same-family associates nearby, there are a few distant clusters. These include five members of the Lucchese family clustered (alone) in Connecticut, a Gambino trio in Washington, DC and 11 members of the Genovese family in Miami. The remaining 293 network members are affiliated with non-NYC families and live outside of the city.

3.2. *Statistical methods and implementation*

For spatial network analysis, we use the 680-member network. However, for measuring degree and node-based properties, we use the original 808-member network, in order to capture the demands (and provisions) of the system on the individuals—and their role across the system—using as much information as possible.

Five SSN methods are created or revived for our analysis (Table 2). First, the cluster/cluster matrix is a scatterplot method comparing network density and network spatial clustering of network subsets. It is used to compare the geographic standard distance ($dist_f$) of a family f's nodes to its network density (d_f), defined as:

$$d_f = \frac{2m_f}{n_f(n_f - 1)} \tag{1}$$

Where m_f is the number of edges in a family's network and n_f is the number of nodes in the family. We regress $dist_f$ and d_f using Pearson's correlation coefficient and report the value. We also compare $dist_f$ and d_f to their respective expected

Table 2. Spatial social network analysis methods

Method (Research Question)	Prior Use	Question Answered
Cluster/Cluster Matrix (1)	N/A	Do tight-knit networks cluster?
Network Density Hotspot (2)	N/A	Are spatial neighbors connected?
Node Role GIS Analysis (3)	Onnela *et al.* (2011), Wang *et al.* (2015)	Are high-degree nodes in special locations?
Route Factor Diagram (4)	Hay (1973), Sarkar *et al.* (2019)	Are network-distant ties dispersed?
Network Flattening Ratio (4)	Sarkar *et al.* (2019)	Is the network spatially efficient?

values. These expectations are derived from permuting the network so ties are joined randomly (per a standard Erdos-Renyi configuration model). The permuted network was configured at size 2-200 to mimic the sizes of the actual families. For each sample size, we run 1,000 permutations (to create a reliably large distribution of results) and take the average standard distance and average edge density for each family size. We use a T-test to compute deviation of $dist_f$ and d_f from the expected value of these quantities in order to describe whether the family unit is more clustered spatially and socially than expected.

Second, in traditional geographic analysis, hotspots represent clusters of individual points, but do not consider the *connectivity* between the spots. Here, we create an exploratory metric of a moving window scan method (Mu and Holloway 2019) that computes link density for nodes only within a local window size. For each node, we calculate the number of nodes and edges within a circular neighborhood radius of 2.34 kilometers in Manhattan distance, which represents a 30 minute walk (Giordano and Cole 2011) and 515 members have at least one person living in this radius from their home. Within the window, the network density, d_i, is the proportion of actual network links to possible links (i.e. if all nodes within the window were connected).

It can be computed as:

$$d_i = \frac{2e_i}{n_i(n_i - 1)} \tag{2}$$

Where e_i and n_i are the numbers of edges and nodes, respectively, in the window surrounding i.

Each node is assigned the percent of other nodes in the moving window who are ties, i.e. the *local density* of the network in the focal window. In general, these reveal which neighborhoods and geographic spaces host social ties, not just of a cluster of individuals.

Third, node role GIS analysis is a general term for the spatial analysis of node features that are derived through the network (e.g. network degree) (Andris 2016). We evaluate whether high degree nodes were in high-income areas, suburban landscapes, or near and points of interest such as ports or subway lines, using a common spatial join. We also examine the distance between node degree (number of connections) and the median center of a node's respective family. A correlation between these two values would appear as:

$$k_i = a * d_E(i, c_f) + b \tag{3}$$

Where k_i is the degree of node i, and $d_E(i,c_f)$ is the Euclidean distance between node i and the centroid (c_f) of family f. This relationship reveals whether popular network members are near the center of the family, wherein more control can be exerted over family members.

Fourth, to examine the spatial clustering and dispersion of the network, we use a route factor ($Q_{i,j}$) diagram, based on the longstanding statistic that compares the Euclidean distance between two nodes to the network distance between them (Hay 1973). The route factor $Q_{i,j}$ between nodes is defined as:

$$Q_{i,j} = d_G(i,j)/d_E(i,j) \tag{4}$$

where d_G is the network (i.e. graph) distance between any pair of nodes i, j. The diagram describes the route factor between every possible pair (as in Sarkar *et al.* (2019)), and reveals the extent to which a pair is more distant in the network if it is more distant in geographic space.

Fifth, we calculate the network flattening ratio (F_s) to measure the network's efficiency of moving information over geographic space, compared to its potential efficiency if optimized for nearness. This ratio involves only distances (no network hops) and relies on a permuted network $\overline{(i,j)}$ that is optimized to minimize total edge distance, while keeping the degree of each node equal to its original degree. The permuted network $\overline{(i,j)}$ is divided by the sum of the original network's edge lengths to produce the network flattening ratio:

$$F_s = \sum d_E\overline{(i,j)} / \sum d_E(i,j) \tag{5}$$

3.2.1. Software and spatial measures

GIS analysis is performed in the ArcGIS 10.5 software environment, and graph analysis is performed in the Gephi Environment and the R Statistical Computing Environment using the iGraph package. Shapefiles are downloaded from the U.S. Census Tiger Line files. All boundaries are from 2010. Accordingly, New York City is defined based on 2010 Metropolitan Statistical Area (MSA) boundaries, which generally match the 1950 New York-Northeastern NJ SMA of 17 counties. The Google Maps API is used to geolocate addresses to coordinates. Median center represents the most central location for each family (as in Bagley 2019). Although the area around the median center may actually be sparsely populated, and thus a poor indicator of an important spatial cluster, increased distance from this center point indicates dispersion from an area where many family members are accessible. To measure income, we use tract-level median household income from the 1960 Decennial Census.

4. Results

4.1. *Family analysis: Spatial patterning of families*

4.1.1. Network tightness and spatial dispersion

The cluster/cluster matrix shows a bivariate tradeoff between maintaining a densely-wired or loosely-wired family and the balance of having members nearby or dispersed (Figure 4). Families exhibit a wide range of network densities and spatial proximities,

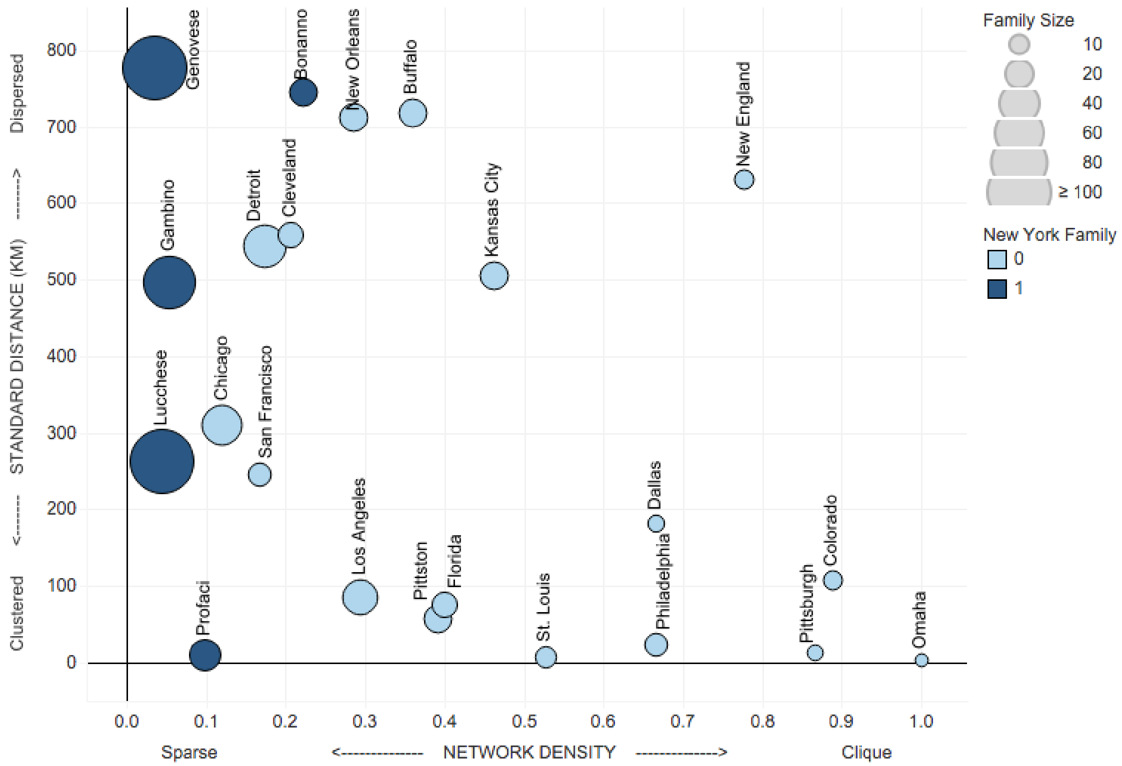


Figure 4. The cluster/cluster matrix shows that large families were sparser but varied in distance while smaller families were denser and closer, though anomalies exist. If families were spatially proximate and densely connected, they would cluster in the lower-right corner. Conversely, if families were spatially dispersed and sparsely connected, they would appear in the upper-left corner.

and this variation differs from expectation. We expected a descending trendline (i.e. with a negative slope), so sparse networks would be dispersed, and tight, clique-like, networks would be clustered. Instead, spatially-clustered families range in network densities, meaning that nearby members of the same family are not necessarily connected. This may mean that the network is not taking advantage of potential ties that could be easy to coordinate. Such local disconnection makes coordination more difficult, but could make the family more secure since even nearby members may not necessarily know (and be able to implicate) one another.

On the other hand, spatially-dispersed families tend toward network sparsity (one exception is the New England family, which maintains a tight network despite members spanning Massachusetts, Rhode Island, and Florida). This geographic dispersion might give a family access to information and opportunities in more diverse locales; when profitable gambling rackets emerged in open territories like Miami and Las Vegas, for example, it would benefit a family to have representatives in these areas. This gives this family—and similar families with this type of dispersion—a foothold in a variety of locales and potential industries.

Yet, compared with the permuted random network, the Mafia network is denser than expected in terms of both geography and the social network. The average standard distance converges at around 1188 km at node sample size n=100. The actual standard distance of the network is much smaller, at a maximum of less than 800 km. The average network density converges at 0.011 at sample size n=42. Families are more connected and tightly-wired than the expectation. Even the sparsest networks, belonging to the Genovese family at 0.036 followed by the Lucchese family at 0.044, have denser networks than would be expected by random chance.

New York City's Genovese family also has the widest standard distance, meaning that its members are distributed widely across the nation. In addition to New York (106) and New Jersey (29), the Genovese family also has members in California (4), Florida (12), and Ohio (1). Conversely, all 11 members of the St. Louis family are found within a standard distance of 6.5 km from the median center. This is a spatially-tight network with an edge density of 0.527. In another example of a geographically-proximate network, the Omaha family only has 4 members, but all are connected, and live within a 1.85 km standard distance.

Yet, not all families who are nearby are densely-connected. The Profaci family, which is clustered in south Brooklyn, surprisingly has a very sparse network, with a density of 0.097 and a standard distance of only 8.32 km. Despite family members living in walking distance of one another, there is surprisingly little conspiring or collaboration among these proximate members. Outside evidence suggests this might be attributable to the relatively strict hierarchical structure of the Profaci family, in which a member's informal position in the family collaboration network closely correlated with the member's formal position in the organizational chart (Krajewski *et al.* 2019); perhaps the strict hierarchical structure left little opportunity for members to form happenstance collaborative ties with their neighbors. We revisit this phenomenon when examining ties in New York City in section 4.2.3.

4.1.2. Correlation with family size

The cluster/cluster matrix suggests that network density may correlate with a third variable, namely family size; the larger the family, the sparser the network. This pattern reflects the organizational structure of large Mafia families, where members were subdivided into 'crews' overseen by a capo (or lieutenant) who in turn reported to the boss or underboss (e.g. Abadinsky 1983, Gambetta 1993, Maas 1969). Since each crew then operates semi-autonomously, there is less need for a dense network spanning all crews in the family. Thus, larger family networks are less tight, and this relationship is better captured by a power-law fit ($R^2 = 0.83$) than a linear fit ($R^2 = 0.36$) via Pearson's Correlation Coefficient. The power-law fit indicates that adding more members to the family causes a significant dissolution of network density whose impacts increase more dramatically with larger networks. While family size is tightly associated with network density, it is a mixed indicator of geographic dispersion, and family size correlates with standard distance with a power law fit of $R^2 = 0.26$ and linear fit of $R^2 = 0.11$.

4.1.3. Dispersion in New York City

In New York City, most members of the same Mafia family live close to one another. At least 80% of members in each family live within 30km of their family's median center. However, there is variation within this relationship: 83% of members of the Bonanno family live within 17 km of the median center, 81% of members of the Gambino family live within 22 km of the median center, 80% of members of the Genovese family live within 30km of the median center, 80% of members of the Lucchese family live within 20 km of the median center, and 84% of members of the Profaci family live within 6 km of the median center. Members of the Profaci family, cluster in in South Brooklyn, tend to live closer to their median center than the members of the other four families, and do not have members that are as far away as that of the other families. The Bonanno, Gambino and Genovese families each have members on the opposite coast.

4.2. *Edge analysis: Locations with sparse and dense ties*

In this section, we examine where local and nationwide edges tend to occur.

4.2.1. Inter-city ties

Most ties stay within a city. There are 625 inter-city ties and 2074 intra-city ties (per MSA boundaries). The most common inter-city ties are those that join Miami and New York City (n = 86 of 4048 possible ties), followed by San Diego and nearby Los Angeles (n = 50 of 121 possible ties), and New York and Detroit (n = 37 of 7040 possible ties). The New York-Miami connection is explained by Miami's status as an open territory available to multiple families; mafiosi operating there came from all five NYC families as well as others. The New York-Detroit connection in part reflects marital connections. The daughter of Detroit mafioso Joseph Zerilli married the son of NYC boss Giuseppe Profaci (Bureau of Narcotics 2007). Zerilli, who formed part of a unique ruling council arrangement in Detroit, was also tied by marriage to several fellow Detroit mafiosi, and several of these in turn formed associational ties with New York-based mafiosi.

As mentioned, the division into families guides the structure of this network. Among all ties, 1814 occur within families and 885 cross families. Family-ties also tend to be closer: The average distance of same-family ties is 166 km (st. dev. 555; range 0.01-3916) while the average distance of cross-family ties is 593 km (st. dev. 1012; range 0.01-3920). This is due to the local nature of families as having a core in a single city and thus, cross-family ties are likely to join two distant cities.

Cross-city ties come with costs and benefits. The clearest benefits to such ties is their ability to efficiently facilitate supply chain management for Mafia rackets requiring the movement of goods. This is especially true for the lucrative drug trade. However, the Mafia's increasing involvement in drug trading and other industries requiring movement of goods around the mid-20th century carried one particularly steep cost: drawing increasing attention from federal law enforcement and congressional committees empowered to investigate issues of this particular brand of 'interstate commerce' (Maas 1969). In addition, a family whose members had many ties to other families might be less secure and more discoverable if one of those other families comes under law enforcement scrutiny.

4.2.2. Satellite members: a common pattern

Families tended to have mostly clustered members, but there were also sometimes 'satellite' members who lived at a distance. As discussed above, family representatives living in another locale rendered them privy to locally-emergent information and trends so they could engage in local profitable rackets. Families tend to feature a core of individuals in a single city, in addition to smaller numbers of representatives in other cities. For example, the NYC-based Lucchese family features two non-Italian associates (Nathan Biegler and Jacob Klein) living on the North Shore of Chicago, the only people in that city who do not belong to the Chicago family. No city has as many distant ties as Miami. The 23 mafiosi residing in the Miami metropolitan area included representatives from nine families: Buffalo, Chicago, Cleveland, Detroit, Florida, Gambino, Genovese, Lucchese and New England. Of these, the Genovese had 11 members, six of whom lived on Miami Beach. Members in Miami also had the highest average betweenness centrality (2271.6) for any city; further, the average degree per city was 7.03, and the highest degree city with more than one individual was Miami (10.9). Interestingly, of the 11 members who lived in San Francisco, the average clustering coefficient is 0. Having sparse local networks in an area means that there may be fewer instances of in-person meetings, trades or stand-offs that could add to local street crime.

4.2.3. Street-level hotspots in New York City

Given the greater ease of associating with neighbors, it would be efficient for neighboring Mafia members to have ties with one another. A moving window analysis is used to examine local, street-level networks in New York City (Figure 5), potentially revealing areas where members and network ties concentrate. In some areas there are no ties between neighbors (evidenced by clusters of grey dots with no edges). For example, in Dyker Heights, home to the Profaci family, a few point members have 4-6 nearby neighbor associates while individuals northeast have no nearby neighbor associates. This distinction puts different narratives on the surrounding built environment—a local connected social network may perpetuate (visible) street-level criminal transactions and meet ups in the space underlying the network ties, in this case, perhaps the Dyker Heights park. Little Italy and the Upper East Side are also home to connected networks of neighbors, resulting in similar network hotspots.

These places could represent conceptual ‘turf’, since nearby members are known associates. If meetings were known to occur near the home, these areas could be cited as strategic locations for law enforcement to patrol in order to intercept known associates meeting one another. In other parts of the city, such as in the Bronx (northeast of the Upper East Side) and the north part of Brooklyn, there are similar numbers of clustered individuals. Using a traditional definition, these individuals (also represented as grey dots) may appear to represent a criminal hotspot, however, because they are not connected, they are a coldspot for network interaction (see Baker *et al.* 2020 for a sensitivity analysis). These locales may still be important to the larger ecosystem since members may have been part of the cross-country supply chain or have interacted with others across the city.

4.3. *Node role analysis: Locations of key network members*

In this section, we report on the home locations of high-degree (i.e. central and well-connected) members of the Mafia network. We intuit that these important individuals could choose where they lived and did so based on some strategy—whether to be close to the family, to oversee some industry, or to live in a desirable (i.e. wealthy) neighborhood for family life. Broadly, the location of high-degree individuals suggests that Mafia families exhibited at least some tendency toward efficiency in the geographic distribution of power and influence, insofar as high-degree members tended to live near the family’s median center (Figure 6).

Members who were farthest from the median center were New York-family members living in California, who tended to have low degree. Several Miami-based agents, who, by default lived far from their family centers (since Miami was an open territory with-

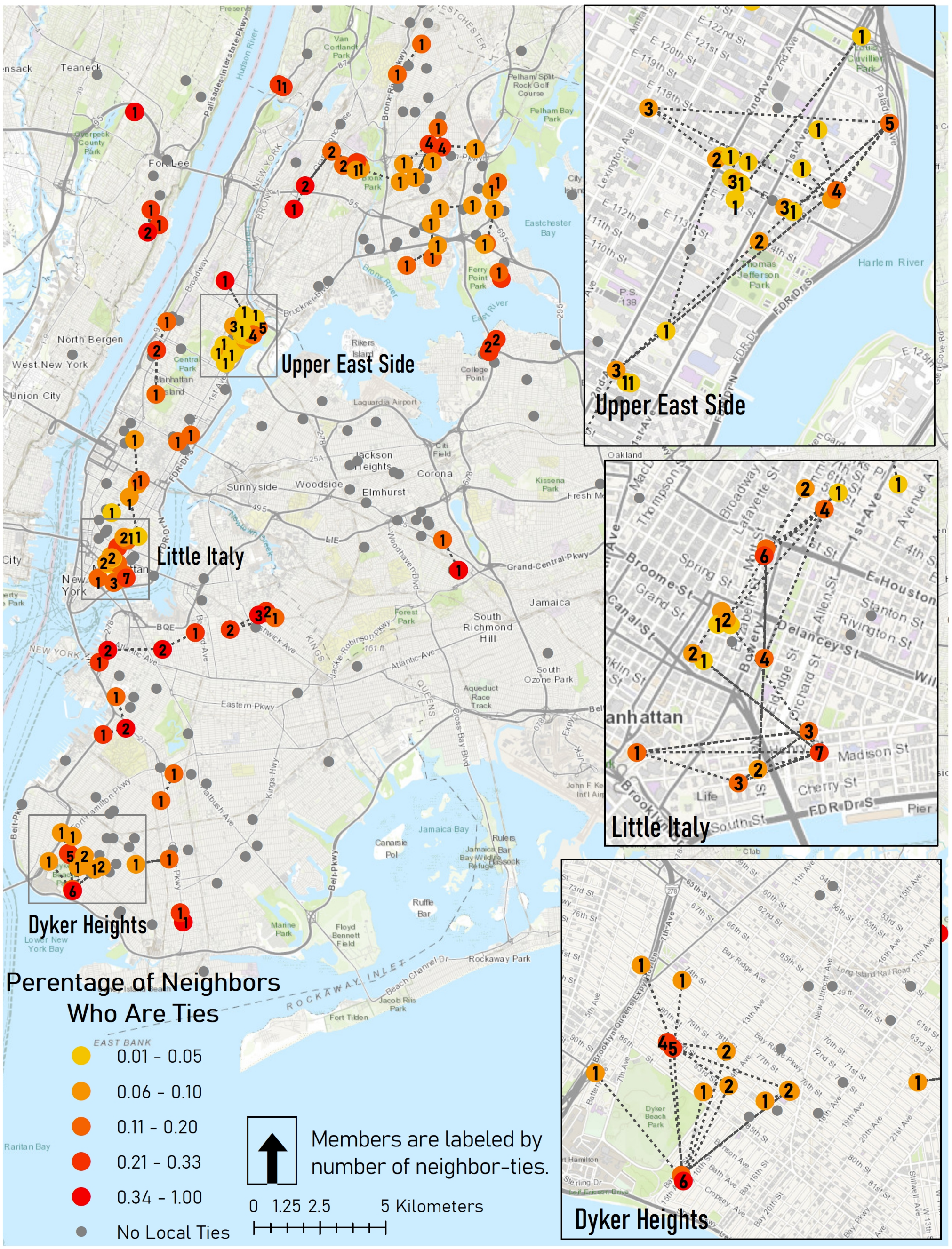


Figure 5. In some parts on New York City, individuals had many ties in walking distance (defined as a 2.34 kilometer buffer using Manhattan distance) while others did not have any ties nearby.

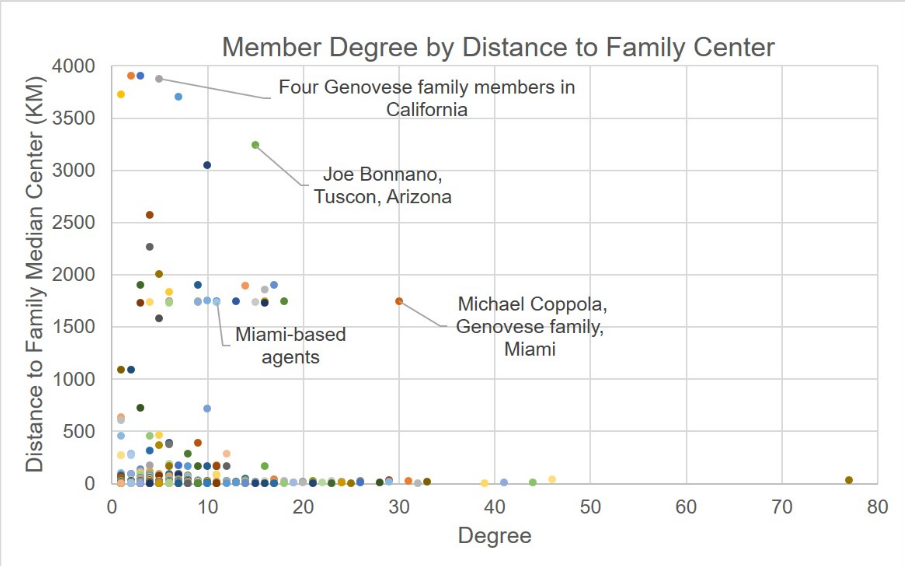


Figure 6. Most network members tended to live near the center of their families. The highest degree network members were locally-embedded. Each member is depicted by a nominal color value.

out a local family), ranged from medium to low degree, except for Michael Coppola, who had a degree of 30. The dossier reports that Coppola was running a 'social club' and was involved in gambling rackets in the Miami Beach area, while being connected to other influential NYC-based mafiosi. Another notable standalone case in Figure 6 is Joe Bonnano, a legendary boss of his eponymous NYC family who by the 1960s had re-located to Tucson, Arizona, both to pursue real estate interests and to escape conflicts with other mafiosi (Maas 1969). In our test of the New York City area, there is no correlation between an agent's degree and the household income of their census tract.

All network members with degree over 40 (i.e. network ties with more than 40 other mafiosi) lived in New York, including John Ormento (Lucchese family capo, degree = 77), Vito Genovese (boss, 46), Anthony Strollo (Genovese family acting boss, 44), Salvatore Santoro (Lucchese family capo, 41). Within New York, Giuseppe Profaci (boss) and Francisco Costiglia (better known as Frank Costello, ex-boss of what later became the Genovese family) each lived within a kilometer of their family's median center (Figure 7), providing potential for control. Another geographic feature of interest is strategic locations near water. Five high-degree New York members lived near open water bodies, which may have been a strategy for intervening with incoming and outgoing shipments (Figure 7). Importing and exporting (of olive oil and cheese from Italy, for example) played a key role in several Mafia industries; further, Mafia control of dockworker and other unions was commonplace (e.g. Bureau of Narcotics 2007).

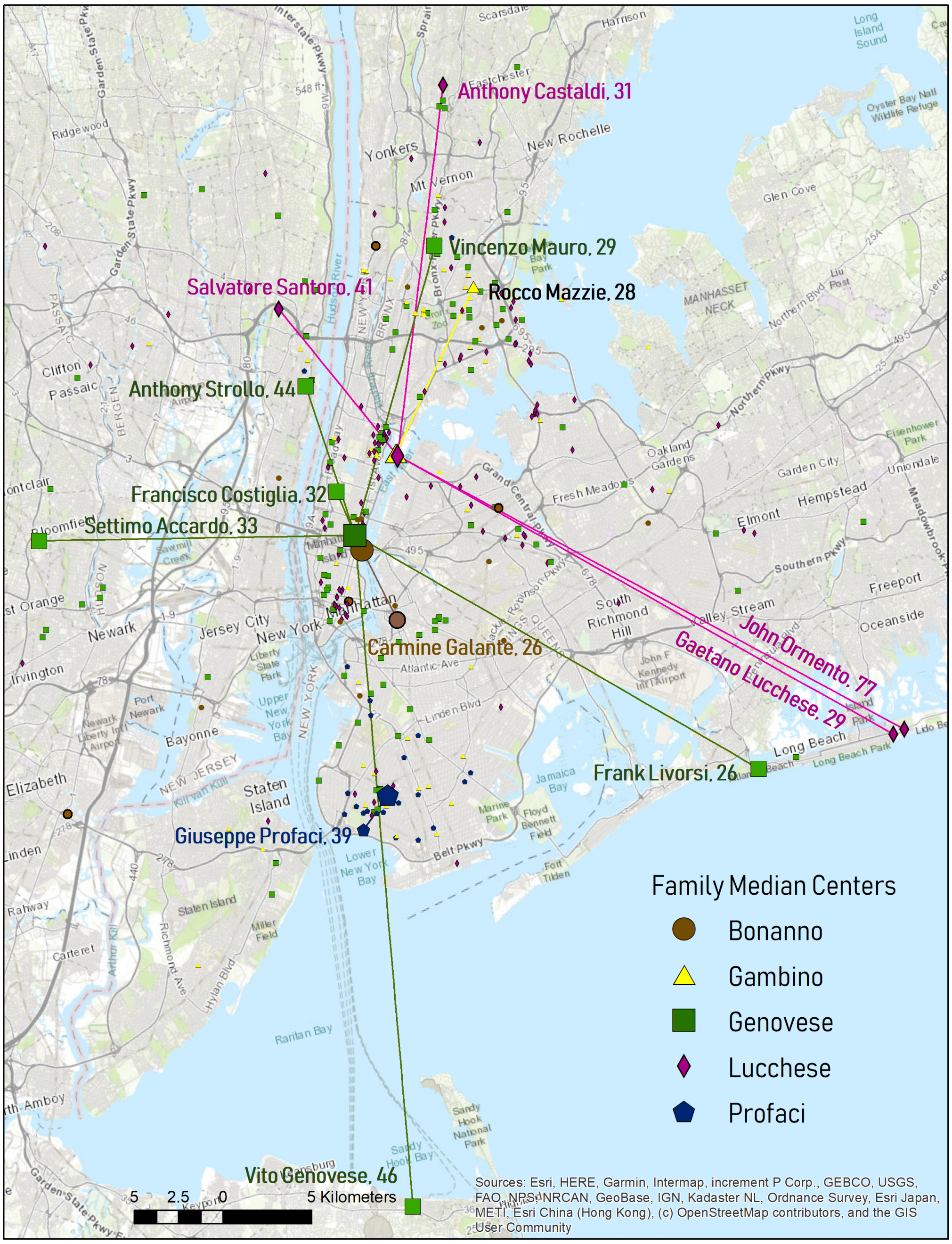


Figure 7. High degree members of each family are marked, and connected to the point centroid of their respective families.

4.4. *Network structure*

4.4.1. Aspatial efficiency

Without regard to spatial configuration, the Mafia network resembles a small-world network, in that it combines high levels of local clustering (i.e. transitivity) with high global connectedness due to inter-cluster ties . Small-world networks have a low average path length and a high clustering coefficient (Watts and Strogatz 1998). In the Mafia network, the average path length (3.89) is lower and the clustering coefficient (.31) is higher than those of a comparable random graph (DellaPosta 2017).

4.4.2. Spatial efficiency

Accounting for spatial network structure, the network flattening ratio for our network is 0.176. This structural metric suggests how far information and people needed to travel to reach their actual connections, compared with a counterfactual scenario in which they simply connected with closer individuals. The flattening ratio for non-family ties is smaller than for the entire network at 0.099, and the ratio when only considering family ties is 0.279, indicating that the family networks are more spatially-efficient.

There are few ways to benchmark this metric, especially because it is derived from a permuted version of its own structure—a common method of benchmarking network characteristics. Other work (Sarkar *et al.* 2019) has used the network flattening ratio, and calculated a ratio of 0.797 for a randomized Poisson-distributed network; this study also examined a network of economic benefits between villagers near Kibale National Park, Uganda, and determined that the network flattening ratio of this network was 0.212. In comparison, the Mafia's within-family ties are more efficiently distributed than this network, but the inter-family Mafia network as a whole is less efficient.

Finally, we measure the route efficiency for all pairs of networks. This measure is the first view into ties-of-ties (i.e. friends-of-friends), called network 'hops'. These transitive ties are important in the Mafia network because they facilitate flow of goods and information from location to location. In this network, pairs with more network hops between them tend to be more distant (Figure 8), especially for cross-family ties. Same-family ties can have a number of hops between them but still be within 50 kilometers of one another—many of these ties reflect the large and sparse New York-based families. An upward trend would indicate that there were few local strangers, and that with increased distance there was little chance of having an associate in common.

5. Discussion and Conclusions

Investigations of the American Mafia's criminal activities at the peak of their operations created a unique data set and opportunity to examine the patterning of this network of individuals. Under the heading of the efficiency-security tradeoff, we find that families clustered and dispersed differently, inter-and intra-city connections were both present, important members tended to live near their families, and that it was common to be disconnected from nearby neighbors. We find a complex network that has mixed characteristics of bi-coastal ties within families as well as strangers who lived on the same block. Additionally, we find a strategic mixture of family members in open cities like Miami likely to facilitate supply chain management. We identify

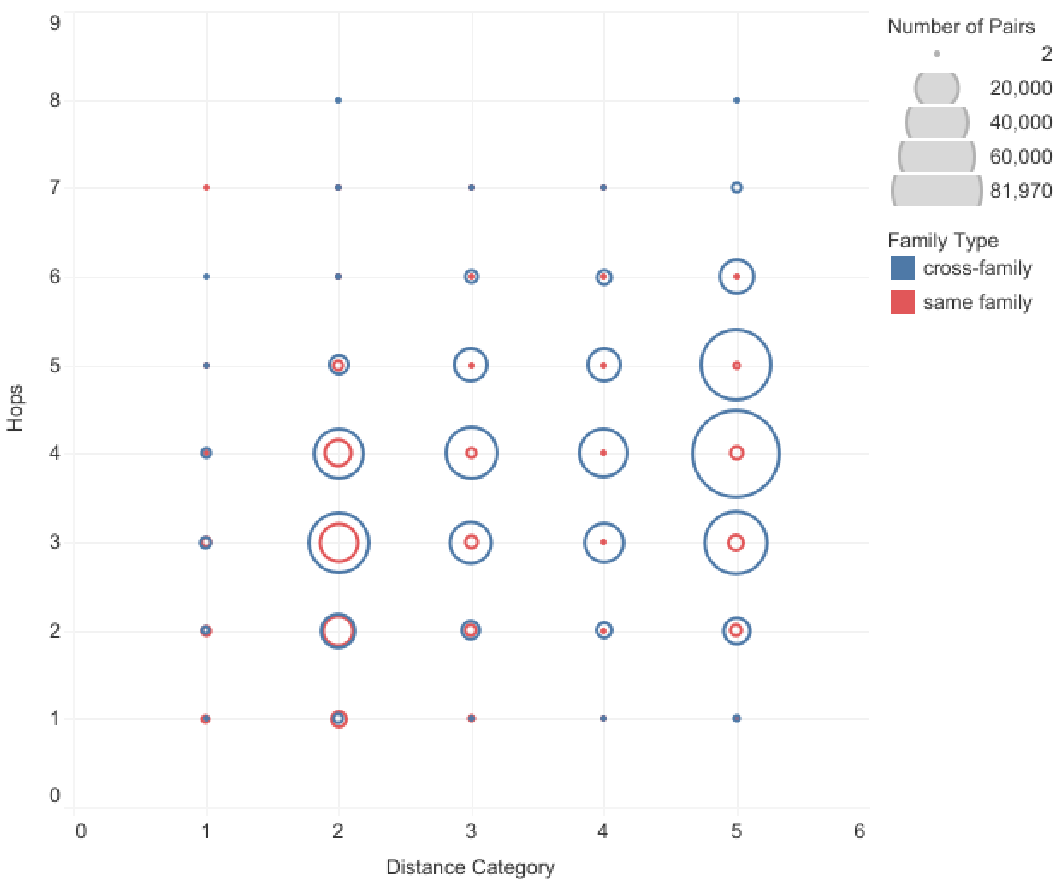


Figure 8. The route efficiency is displayed for each possible pair. Distance bins (in kilometers) are the following: 1 (0-2.34), 2 (2.34-50), 3 (50-500), 4 (500-1000), 5 (1000+).

high-degree individuals' tendency to live near the center of their respective families, as well as on the coast. Finally, we find that family-based ties were more spatially efficient than non-family based ties, indicating the important role of organizational membership.

From a methodological perspective, the advances made here in modeling social networks within geographic space help us better understand the spatial and network proclivities and strategies used by organized crime families. These new metrics, such as the *cluster/cluster matrix* and *moving window network analysis*, and re-invigoration of the *flattening ratio* are helpful because they reveal patterns that would otherwise be harder to detect and quantify. For example, the cluster/cluster matrix reveals variation in families' network density and spatial proximity so that not all cliques are highly clustered and not all sparse networks are dispersed. The moving window network analysis shows that areas that would mathematically be considered as hot spots of criminals by their clustered location only, may not be as important as the hot spots where people are connected. The outcome of our analysis suggests a new understanding, and reinforces existing understandings of crime families' strategic use of geographic space, distance, features, and potential missed opportunities (e.g., living close together but not connected could be a strategy to avoid detection or a missed opportunity for collaboration). Since organized crime groups, from biker gangs to terrorist networks, face similar efficiency-security tradeoffs, future work can examine the generalizability of the patterns reported here.

The metrics developed can also be applied more broadly to SSNs. They contribute to the field of GIScience by providing a technique that allows a point pattern to have connected points, illustrating a conceptual closeness between points that cannot be captured by distance. These methods can be scaled to other systems. For example, they can be used to choose a city for a new firm opening in order to maximize network access, but minimize cumbersome travel (van Meeteren *et al.* 2016). The novelty of this GIS analysis lies in that it analyzes geolocated agents with known bonds that have a specific purpose, goal, and outcome.

There are several limitations to our analysis. The dataset does not contain all actors, or family members, and the nomination process may be incomplete (i.e. perhaps some members had ties that were not identified in the dataset). Next, we can only see the residues of Mafia location strategy by analysing their spatial patterns, and as such, it is difficult to distinguish organizational strategy from individual actions. Even if we were to find an extremely clustered or extremely distributed network, we cannot tell whether this structure emerged from top-down directives (i.e. orders from powerful bosses) or from individual decisions (i.e. seeking out beneficial collaborations), though previous research suggests the latter may be at least as relevant as the former (Gambetta 1993, Abadinsky 1983, Reuter 1983).

Further, we lack information about where or if particular crimes were committed, though other research finds that city-level density of Mafia members correlated positively with crime rates (Mastrobuoni and Patacchini 2012). The geographic 'hot spots' that emerge most clearly in our analysis (Figure 5) also lend face validity; areas like Little Italy, the Upper East Side, and Brooklyn were often identified as Mafia hotbeds in historical accounts from this time period (Maas 1969). Still, business—whether shipping, running a protection or gambling racket, or managing a store front business—may not have been conducted at the member's residential address. For example, mafiosi often used bars and restaurants as fronts for gambling rackets and legal import-export businesses to smuggle drugs (Maas 1969). Finally, we also lack contextual information about the built environment in the 1960s, such as locations for meeting and sharing information, which may be important for recreating the landscape of Mafia activity. Further research and qualitative accounts could better explain why families chose their particular geographic configuration.

Despite shortcomings, the story told in this manuscript illustrates how geographic information science can be a useful vantage point for learning about characteristics of a complex organizational system like the Mafia, and for social networks more broadly.

Data and codes availability statement

The data that support the findings of this study are available at figshare.com at https://figshare.com/s/7873c6e4534129aabea1.

Note(s)

A few notable members were removed from the our network due to lack of U.S. addresses: Settimo Accardo (degree k=39) was a fugitive from the government after violating narcotic laws, Salvatore Lucania (k=79) was exiled to Italy, and Francesco Coppola (k=34) was deported to Italy.

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