Structural and Ethnic Dynamics in Criminal Networks: A Comparative Study of Italian and London Gangs

Carlotta Nunziati, MSc in Computer Science, 0001181860
Joana Pimenta, MSc in Artificial Intelligence, 0001168774
Leonardo Vorabbi, MSc in Computer Science, 0001186597
Alexandru Nicolescu, MSc in Computer Science, 0001186762
Daniele Algeri, MSc in Artificial Intelligence, 0001196298

1 Introduction

The present study is situated within the field of social sciences, focusing on the use of Social Network Analysis (SNA) to examine covert criminal organizations. In this work, we carry out a comparative analysis of two covert criminal networks (one in Italy and one in London) to highlight their structural and sociocultural differences. The datasets used for this study, the Italian Gang Network (67 nodes, 114 edges) (available online at [3]) and the London Gang Network (54 nodes, 315 edges) (available online at [4]), map internal relationships and include a shared metadata attribute: the nationality of each individual.

2 Problem and Motivation

The study aims to compare the structural and social dynamics of two covert criminal networks, one Italian and one London-based, to understand how relational structure and ethnic/national composition influence internal organization and group resilience. Historically, researchers often overlooked gangs as collective entities, focusing instead on the traits of individual members [10]. As a result, the connection between gang activity and gang structure has remained largely unexplored, described as a “black box” [5]. Nevertheless, a small but expanding literature on gangs and social networks has emerged, based on the idea that “human relationships form the least common denominator for organized crime” [11].

Klein and Maxson [9] highlight that "ethnicity is one of the most widely discussed, and little studied, aspects of gangs." Ethnic groups, defined by shared heritage, culture, language, religion, or country of birth [15], play a central role in gang dynamics. Research has consistently shown that ethnicity is a key factor in both gang formation and membership [1] [2] [7] . While ethnic diversity has been recognized as influential in broader community contexts [13], its specific relationship to gang activity and internal organization remains largely unexplored [16]. The project therefore addresses two key issues:

Structural organization and internal dynamics: Analyze how individual positions and relational patterns affect the stability and hierarchy of covert criminal networks.

Sociocultural dimension: Examine how national composition (members' nationality) shapes connection patterns, leadership, and cooperation within criminal organizations.

To achieve these aims, the project adopts a Social Network Analysis (SNA) approach, which has a long-standing tradition in gang and organized crime research [8] [14]. Technological advancements have significantly expanded its potential [6] [12]. Reconstructing a gang as a social network involves linking each unit (whether a group or an individual) according to the type of relationship under investigation [17]. This approach advances the theoretical use of Social Network Analysis in criminology and provides practical insights for security policies and investigations by identifying key nodes and structural vulnerabilities. While prior research often focuses on individual networks, comparative studies across sociocultural contexts are rare. Understanding how relational structures and cultural factors shape organizational resilience can guide policymaking, intelligence analysis, and law enforcement in detecting central actors, weak points, and cohesive subgroups in covert operations.

The main contributions of the project include:

1. Comparative Perspective: Systematic comparison of Italian and London-based covert criminal networks to highlight structural and social differences.

2. Structural and Sociocultural Integration: Analysis of network metrics alongside nationality to understand the impact of social identity and homophily on organization and leadership.

3. Network Robustness Insights: Assessment of cohesion and vulnerability to node removal to reveal how criminal organizations sustain resilience.

3 Datasets

Our analysis uses two publicly available datasets from the UCINET project: the **London Gang Network** (54 nodes) and the **Italian Gangs Network** (67 nodes) [4, 3]. Both datasets provide 1–mode person–person adjacency matrices together with node attributes, and are fully digitised.
The **London** dataset consists of a 54×54 undirected valued matrix. Nodes represent gang members, and edges encode the presence and strength of criminal or social relations (e.g. co-offending, spending time together, shared crew membership).
The **Italian** dataset is a 67×67 undirected adjacency matrix. Nodes correspond to individuals involved in mafia-related activities, while edges represent generic relational ties within the organisation (collaboration, interaction, or shared illicit activities).
In both cases, nodes represent individuals and edges represent the social or criminal connections among them, forming the structural basis for our network analysis.

3.1 Digitisation and Data Handling

For this study, each adjacency matrix was stored in CSV format (`LONDON_GANG.csv` with a 54×54 matrix; `ITALIAN_GANGS.csv` with a 67×67 matrix).
It is important to note that the original London dataset contained weighted edges representing the strength of ties: 1 (hang out together), 2 (co-offend together), 3 (co-offend together, serious crime), and 4 (co-offend together, serious crime, kin). However, to ensure structural comparability with the Italian network, which is an unweighted graph, these weights were removed.

The London network was thus binarized, treating all values ≥ 1 as a simple connection (1) and absence of ties as 0.
The London attributes file (`LONDON_GANG_ATTR.csv`) lists `Age`, `Birthplace`, `Residence`, `Arrests`, `Convictions`, `Prison`, `Music`, and `Ranking`; the Italian attributes file (`ITALIAN_GANGS_ATTR.csv`) includes `Nationality/Country of origin`. To ensure consistency between the two metadata structures and enable cross-network comparisons, we restricted our analysis to a single, conceptually aligned attribute capturing individuals' origin (London `Birthplace`; Italian `Nationality/Country of origin`). Data handling was performed in **Python** with `pandas`, using `pandas.read_csv` to load matrices and attributes into `DataFrames`.

3.2 Computing Measures

Network measures were computed with `NetworkX`. The adjacency `DataFrames` were converted into graph objects via `nx.from_pandas_adjacency`, which then served as the basis for all subsequent analyses and visualisations.

4 Validity and Reliability

4.1 Validity (Representation of Reality)

The model of the dataset—a graph of 54 nodes and 315 edges—is a structural abstraction of a complex, real-world social system. The validity, or how closely this model represents reality, is subject to several key considerations:

- **Incompleteness of Covert Data:** The dataset maps a "covert network." By definition, such networks are hidden. The data (likely sourced from surveillance or police records) is almost certainly an incomplete snapshot. We must assume that some real-world relationships were unobserved and are missing from the model.
- **Static vs. Dynamic Reality:** The dataset represents the network at a single point in time. Real-world social structures are dynamic, with ties forming, dissolving, and changing in strength. Our model does not capture this temporal evolution.
- **Unweighted Analysis of Weighted Data:** The source data is weighted with discrete values (such as 1, 2, and 3), which represent the strength of the relationship. In our analysis, we employed standard, unweighted measures (e.g., `nx.density`, `nx.diameter`, `nx.degree_centrality`). This was an intentional choice to focus purely on the **topological structure**, but it is a significant simplification. The model treats a strong, frequent bond as equivalent to a weak, infrequent one, which impacts the real-world interpretation of influence and cohesion.

In summary, the model is a valid (as it is academically vetted) but simplified, static, and unweighted representation of the network's topology, not a complete or dynamic reflection of its real-world social complexity.

4.2 Reliability (Reproducibility)

The reliability of this study (the ability for another researcher to reproduce the exact same results) is **high**. This is ensured by the methodology used to treat the data:

- **Public Data:** The dataset was sourced from a stable, public, and citable URL. Any researcher can access the exact same source files in [4] [3].
- **Open-Source, Deterministic Tools:** The entire analysis was conducted using open-source Python libraries (`pandas` and `NetworkX`). The functions used for calculating measures (`nx.density`, `nx.betweenness_centrality`, etc.) are deterministic. Given the same input graph, they will produce the identical output every time.
- **Transparent Workflow:** The data treatment was minimal and explicit: loading the CSV via `pandas`, handling indices, converting it to a `NetworkX` graph, and applying specific functions. This step-by-step process can be scripted and shared, ensuring perfect reproducibility.

Overall, while the datasets provide only partial depictions of real-world social structures, the analytical process applied to them is transparent, stable, and highly reproducible.

5 Measures and Results

For both the Italian and London gangs, we study the same network metrics and compare them. We start by analyzing **general structural metrics**, which quantify the overall organization and efficiency of the network:

General Structural Metrics

- **Density** (D): it measures the fraction of all possible edges in the graph that actually exist.

$$D = \frac{2m}{n(n-1)} \tag{1}$$

  where m is the number of existing edges and n the number of nodes. In our networks, density reflects how globally interconnected the criminal gang is. High values of density indicate that overall, criminals maintain many direct relationships with other members.

- **Average degree** ($\langle k \rangle$): the mean number of connections per node.

$$\langle k \rangle = \frac{1}{n}\sum_{i=1}^{n} k_i = \frac{2m}{n} \tag{2}$$

  In our networks, it measures the average number of relationships that criminals maintain, capturing their social activity and exposure.

- **Network diameter** (D_{max}) and **average path length** (ℓ): respectively, the maximum and the mean of the shortest path distances between all node pairs.

$$D_{max} = \max_{i,j} d_{ij} \tag{3}$$

$$\ell = \frac{1}{n(n-1)}\sum_{i \neq j} d_{ij} \tag{4}$$

  In our networks, these two measures offer insights into the communication distances between criminals and how efficiently information can propagate through them.

- **Clustering coefficient (C)**: expresses the probability that two neighbors of a node are connected, revealing local cohesion or closed "cells". For node i:

$$C_i = \frac{2t_i}{k_i(k_i - 1)} \tag{5}$$

  where t_i is the number of triangles passing through i. The overall clustering coefficient is the average of C_i across all nodes:

$$C = \frac{1}{n}\sum_{i=1}^{n} C_i \tag{6}$$

  In our networks, it measures the cohesivenes of local operational cells formed by interconnected criminals.

- **Modularity (Q)**: quantifies the presence of well-defined communities:

$$Q = \frac{1}{2m}\sum_{ij}\left(A_{ij} - \frac{d_j d_i}{2m}\right)\delta(g_i, g_j) \tag{7}$$

  where m is the total number of edges, A_{ij} is the adjacency matrix, d represents node degrees, and $\delta(g_i, g_j)$ is the Kronecker delta (1 if nodes i and j share the same birthplace group, 0 otherwise). In our networks, it captures the extent to which criminals tend to organize themselves into distinct subgroups with limited interaction between them.

Centrality Metrics

We also compute **centrality metrics**, which identify key actors based on different notions of importance:

- **Degree centrality ($C_D(i)$)**: number of direct ties a node has.

$$C_D(i) = k_i \tag{8}$$

  In our networks, it reveals the most active or influential criminals, based on the number of relationships with other members.

- **Betweenness centrality ($C_B(i)$)**: measures how often a node lies on the shortest paths between others.

$$C_B(i) = \sum_{s \neq i \neq d} \frac{\sigma_{sd}(i)}{\sigma_{sd}} \tag{9}$$

  where σ_{sd} is the number of shortest paths between s and d, and $\sigma_{sd}(i)$ those passing through i. In our networks, it highlights how much criminals can act as brokers or gatekeepers.

- **Closeness centrality ($C_C(i)$)**: reciprocal of the mean distance from a node to all others.

$$C_C(i) = \frac{n-1}{\sum_{j \neq i} d_{ij}} \tag{10}$$

  In our networks, this measure offers insight into how efficiently a criminal can reach, or be reached by, the rest of the gang.

- **Eigenvector centrality** ($C_E(i)$): assigns importance based on being connected to other important nodes.

$$C_E(i) = \frac{1}{\kappa} \sum_{j=1}^{n} A_{ij} C_E(j) \tag{11}$$

  where κ is the largest eigenvalue of the adjacency matrix A. It identifies leaders recognized by other influential members and, in our networks, it measures how embedded a criminal is within the main core structures of the organization.

Roles and Network Hierarchy

Based on these metrics, we classify network roles as follows:

- **Leaders**: nodes in the top 5% for both degree and eigenvector centrality, broadly connected and influential.
- **Brokers**: nodes in the top 5% for betweenness, key intermediaries between subgroups.
- **Peripherals**: nodes in the bottom 5% for degree, few connections and limited influence.

We further analyze the ***k*-core decomposition** to inspect hierarchical structure and power concentration. A k-core is a maximal subgraph where each node has degree $\geq k$. The *main core* corresponds to the highest k with non-empty core.
We also assess **network robustness** by comparing metrics (density, average path length, k-core) before and after removing central nodes, in order to study the structural impact of node removal.

Attribute-based Network Analysis

Finally, to explore how ethnic background shapes internal organization, we perform **attribute-based network analyses** based on the *Birthplace* attribute.

- **Assortativity (Modularity Q) and mixing matrix**: used to quantify the extent of homophily by *Birthplace*. For unordered characteristics, assortativity is measured as the modularity Q [7] indicating the extent to which similar nodes connect to each other.
- **Centrality by group**: comparing average degree, betweenness, and eigenvector centrality across ethnic categories reveals whether certain groups occupy more central positions.
- **Community composition and diversity**: community detection via modularity maximization; ethnic heterogeneity measured with the **Shannon Diversity Index**:

$$H = -\sum_{i} p_i \log(p_i) \tag{12}$$

  where p_i is the proportion of members from group i within a community. Higher H values indicate more diverse communities.
- **Inter-group connectivity**: proportion of edges linking individuals of different birthplace categories, indicating cross-ethnic integration.
- **Subgraph analysis by birthplace**: evaluation of intra-group cohesion through internal density and clustering coefficient.

Note: Since the Italian network is disconnected, metrics such as diameter and average path length are computed on the largest connected component, including cases where central nodes are removed.

5.1 Italian Gang Analysis

This section will report the results of the metrics introduced at the beginning of section 5, with respect to the Italian gang network.

5.1.1 Structural analysis

In figure 1 a plot of the network is shown, where each node is colored according to its *Country* label.

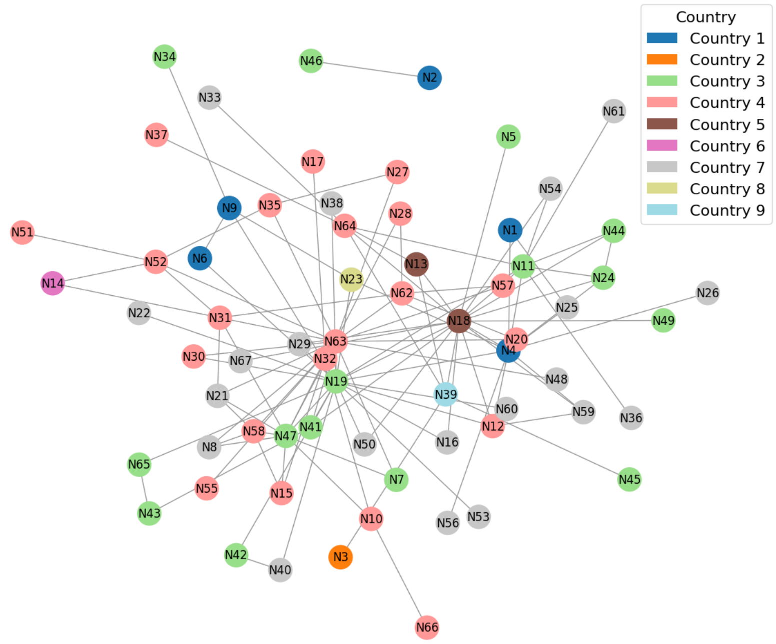


Figure 1: Italian Network graph visualization. Each node is colored according to its country label

Macro-level Cohesion and Structure

The following table reports the values of the structural metrics for the Italian Network. Since the network is not connected and diameter and average path length are not defined for disconnected networks, we instead calculate these metrics for the largest connected component, which has 65 nodes (out of 67).

Metric	Result
Density	0.0516
Average Degree	3.0430
Average Path Length (largest connected component)	3.012
Diameter (largest connected component)	6
Avg. Clustering Coeff.	0.4347
Modularity	0.5561

Micro-level Centrality and Social Roles

The following tables illustrate which nodes occupy the social roles of *Leaders*, *Brokers* and *Peripheral Members*, based on their centrality metric values, which are also reported in the tables.

Leaders The most influential, connected, and central members.

Node	Degree	Betweenness	Closeness	Eigenvector
19	0.3182	0.5558	0.5397	0.4394
63	0.2879	0.3633	0.4597	0.3110
18	0.2727	0.2881	0.4563	0.3784

Table 1: Leader nodes (Degree ≥ 0.1621 & Eigenvector ≥ 0.2542)

Brokers Members who act as "bridges" connecting different parts of the network.

Node	Degree	Betweenness	Closeness	Eigenvector
19	0.3182	0.5558	0.5397	0.4394
63	0.2879	0.3633	0.4597	0.3110
18	0.2727	0.2881	0.4563	0.3784
47	0.1515	0.1396	0.4280	0.2177

Table 2: Broker nodes (Betweenness ≥ 0.1369)

Peripheral Members Marginal members with few connections, existing on the network's edges.

Node	Degree	Betweenness	Closeness	Eigenvector
2	0.0152	0.0000	0.0152	0.0000
3	0.0152	0.0000	0.2443	0.0132
5	0.0152	0.0000	0.3119	0.0556
17	0.0152	0.0000	0.2463	0.0141
22	0.0152	0.0000	0.3487	0.0645
26	0.0152	0.0000	0.2941	0.0384
33	0.0152	0.0000	0.2473	0.0179
34	0.0152	0.0000	0.2619	0.0140
36	0.0152	0.0000	0.2941	0.0349
37	0.0152	0.0000	0.2473	0.0179
38	0.0152	0.0000	0.3487	0.0645
45	0.0152	0.0000	0.2443	0.0132
46	0.0152	0.0000	0.0152	0.0000
48	0.0152	0.0000	0.3134	0.0457
49	0.0152	0.0000	0.3119	0.0556
51	0.0152	0.0000	0.2434	0.0117
53	0.0152	0.0000	0.3487	0.0645
55	0.0152	0.0000	0.3134	0.0457
56	0.0152	0.0000	0.2941	0.0384
60	0.0152	0.0000	0.3487	0.0645
61	0.0152	0.0000	0.2941	0.0349
66	0.0152	0.0000	0.2324	0.0069
67	0.0152	0.0000	0.3119	0.0556

Table 3: Peripheral nodes (Degree ≤ 0.0152)

Hierarchy and Vulnerability

These measures test the power structure and resilience of the network.

K-Core Decomposition The most densely connected "core" of the network is identified. The analysis reveals a main core with a **k-value of 3** that consists of **20 nodes** (out of 63). The nodes in this core are: `[4, 8, 11, 12, 13, 15, 18, 19, 21, 24, 31, 32, 39, 41, 44, 47, 58, 59, 63, 64]`.

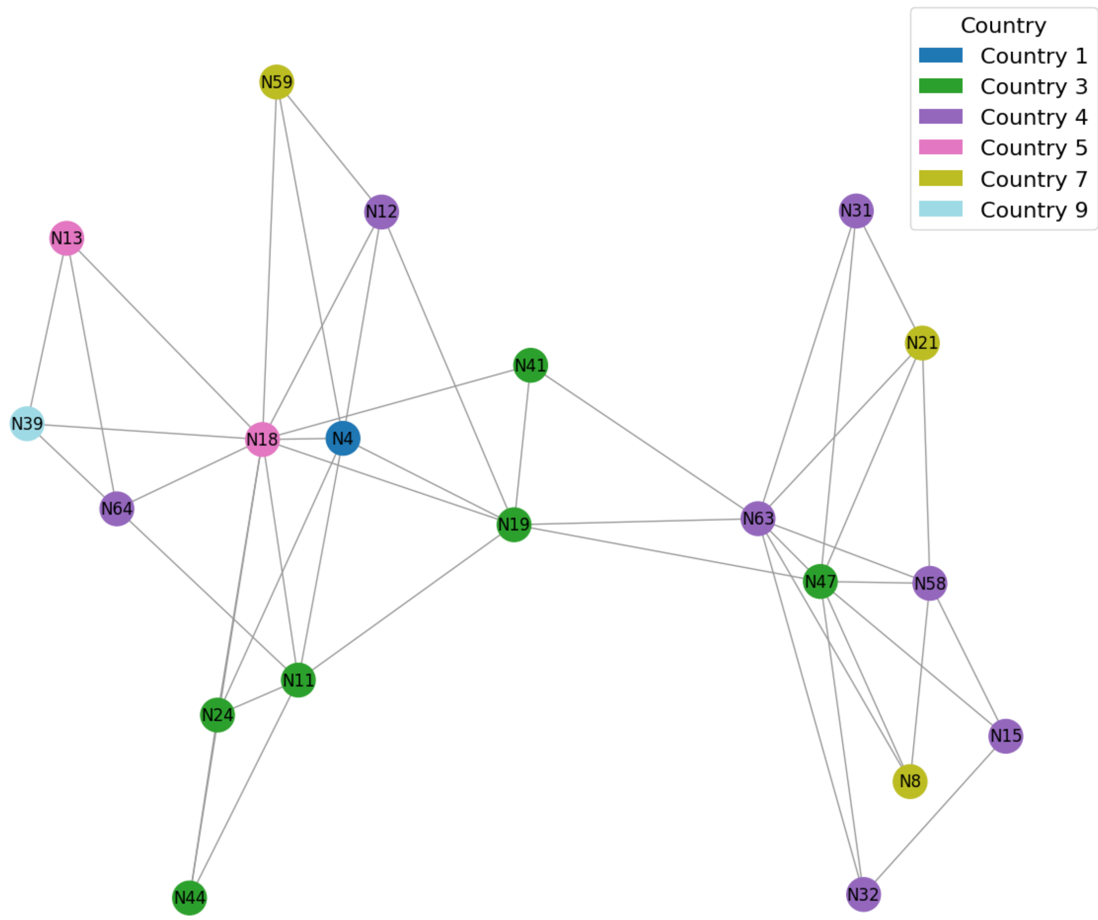


Figure 2: Core of Italian Network graph visualization.

Vulnerability Simulation Removing the three identified leaders (19, 63, 18) had a clear impact on the network structure. After their removal, the network broke into 18 components, and the largest connected part dropped from 65 to 24 nodes, showing a strong loss of cohesion. The density decreased from 0.0516 to **0.0288**. The average shortest path length increased from 3.0120 to **3.1341** (a **4.05%** rise), indicating slightly longer communication chains among the surviving nodes.

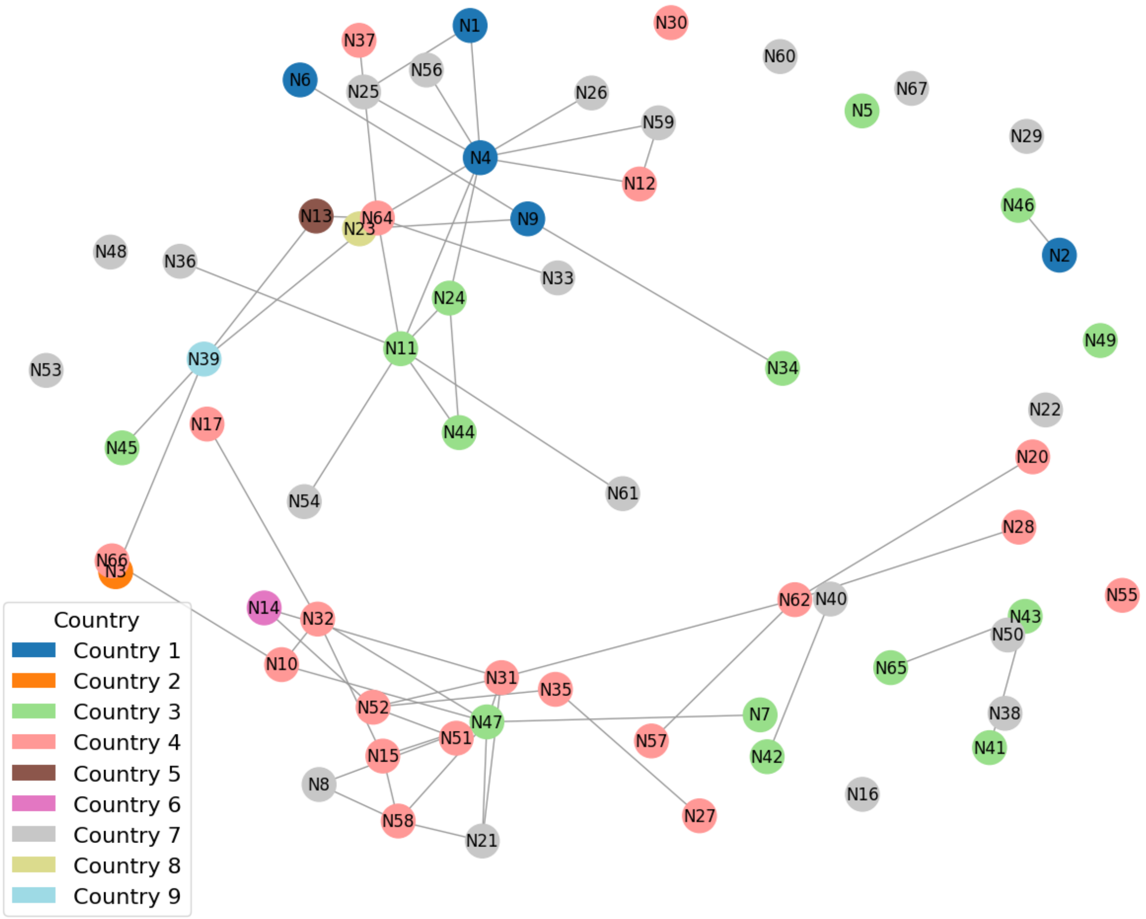


Figure 3: Italian Network sub-graph visualization without leaders.

In summary, the **Italian gang network** is sparse but moderately cohesive, with clear community divisions and a defined inner core (**k = 3**). Leadership is concentrated in a few nodes (19, 63, 18), supported by brokers who link subgroups. When these leaders are removed, the network becomes **fragmented**, revealing limited redundancy and a **moderate structural vulnerability** despite its local cohesion.

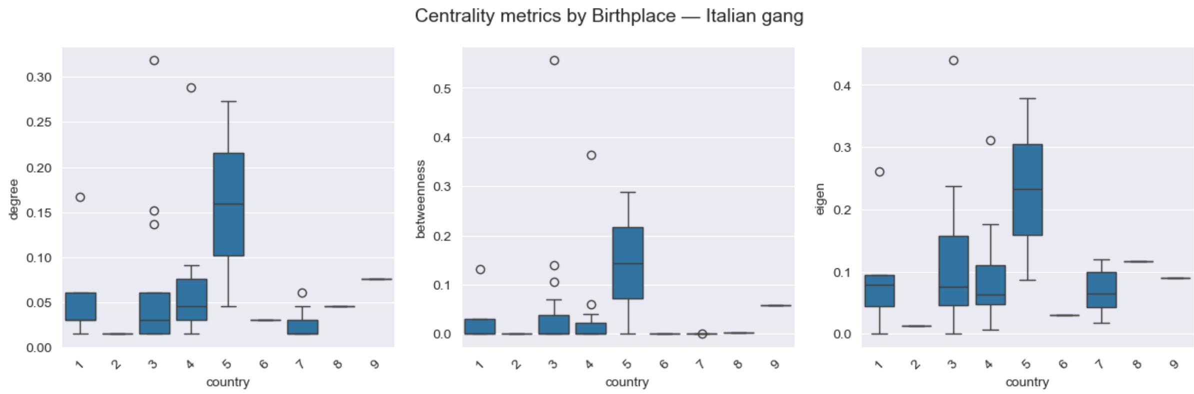
5.1.2 Ethnicity and Community Analysis

The Italian gang network shows a **moderate level of ethnic homophily**, with an assortativity coefficient of 0.150. This indicates a slight preference for forming ties with individuals sharing the same *Birthplace*, while the network as a whole remains well integrated.
The **mixing matrix** supports this interpretation: diagonal values are relatively high for groups 3, 4, and 5, reflecting intra-group cohesion, but many off-diagonal values remain substantial, revealing frequent **cross-ethnic interactions**.

	1	2	3	4	5	6	7	8	9
1	0.018	0.000	0.031	0.004	0.004	0.000	0.022	0.009	0.000
2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.004
3	0.031	0.000	0.096	0.053	0.031	0.000	0.061	0.004	0.004
4	0.004	0.000	0.053	0.228	0.013	0.009	0.035	0.000	0.004
5	0.004	0.000	0.031	0.013	0.009	0.000	0.026	0.000	0.009
6	0.000	0.000	0.000	0.009	0.000	0.000	0.000	0.000	0.000
7	0.022	0.000	0.061	0.035	0.026	0.000	0.000	0.000	0.000
8	0.009	0.000	0.004	0.000	0.000	0.000	0.000	0.000	0.000
9	0.000	0.004	0.004	0.004	0.009	0.000	0.000	0.000	0.000

Table 4: Mixing matrix (proportion of connections between Birthplace groups) – Italian gang

Analysis of **centrality** shows clear differences among groups. Group 5 emerges as the most central, with the highest degree (0.159), betweenness (0.144), and eigenvector value (0.233). Groups 3 and 9 also show moderate centrality, suggesting intermediate structural roles, while groups 2, 6, and 7 appear more peripheral.



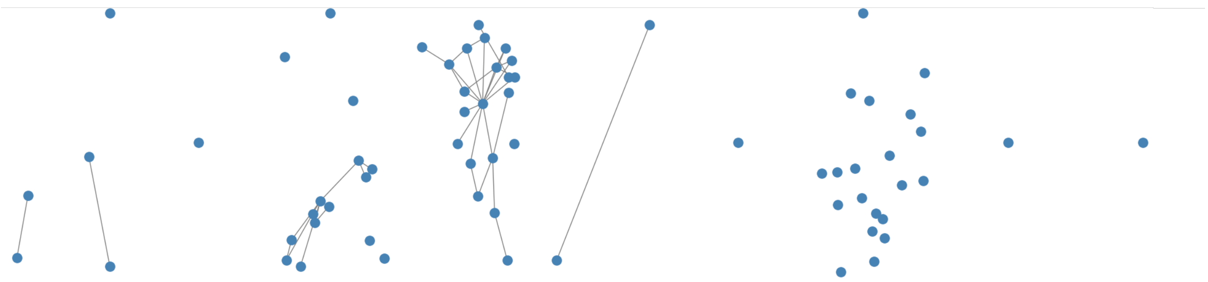
The **community analysis** identifies five communities with varying levels of diversity. Most are ethnically mixed, with the exception of community 4, dominated by groups 1 and 3. The mean Shannon index ($H = 1.174$) indicates **high community heterogeneity**.

A significant proportion of ties (64.91%) connect individuals from different *Birthplace* categories, confirming a high degree of **cross-ethnic integration**. Thus, ethnic background does not represent a major organizational force within the network.
Subgraph analysis highlights additional structural differences:

- Group **4** forms the largest and most cohesive internal cluster (21 nodes, density = 0.124).
- Group **5**, although consisting of only 2 members, is fully connected (density = 1.000).
- Groups **6–9** show little to no internal connectivity, relying mainly on cross-group ties.

Birthplace	Nodes	Edges	Density	Clustering
1	5	2	0.200	0.000
2	1	0	0.000	0.000
3	15	11	0.105	0.156
4	21	26	0.124	0.294
5	2	1	1.000	0.000
6	1	0	0.000	0.000
7	20	0	0.000	0.000
8	1	0	0.000	0.000
9	1	0	0.000	0.000

Table 5: Subgraph-level statistics by Birthplace – Italian gang



In summary, the Italian gang shows **moderate homophily** but remains **highly integrated**. Most collaboration occurs across different national backgrounds, and ethnicity plays only a **secondary role** in shaping the network's structure.

5.2 London Gang Analysis

This section will report the results of the metrics introduced at the beginning of section 5, with respect to the London gang network.

5.2.1 Structural analysis

In figure 4 a plot of the network is shown, where each node is colored according to its *Birthplace* label.

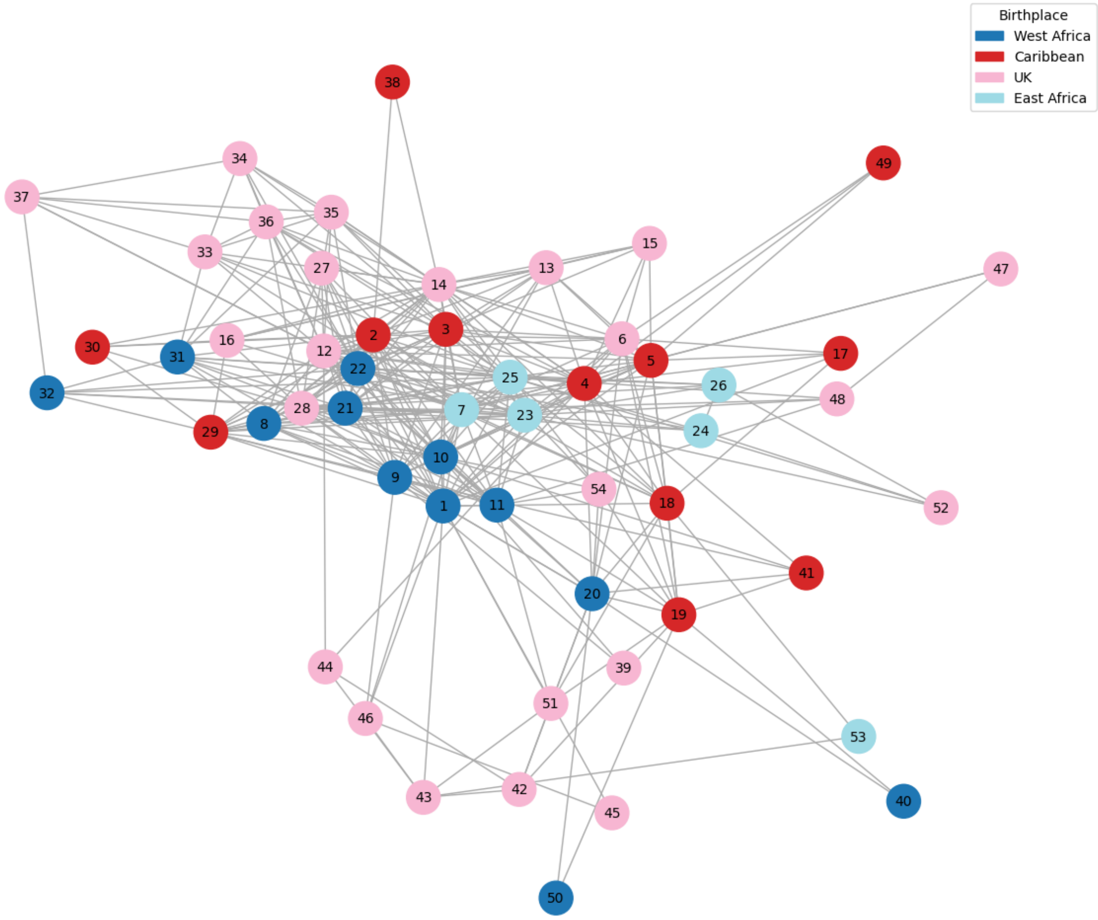


Figure 4: London Network graph visualization. Each node is colored according to its birthplace label

Macro-level Cohesion and Structure

The following table reports the values of the structural metrics for the London Network.

Metric	Result
Density	0.2201
Average Degree	11.67
Average Path Length	2.05
Diameter	4
Avgerage Clustering Coefficient	0.6331
Modularity	0.2665

Micro-level Centrality and Social Roles

The following tables illustrate which nodes occupy the social roles of *Leaders*, *Brokers* and *Peripheral Members*, based on their centrality metric values, which are also reported in the tables.

Leaders The most influential, connected, and central members.

Node	Degree	Betweenness	Closeness	Eigenvector
1	0.4717	0.1087	0.6543	0.2367
7	0.4717	0.0755	0.6543	0.2433
12	0.4717	0.0596	0.6386	0.2494

Table 6: Leader nodes (Degree $\geq$ 0.4594 & Eigenvector $\geq$ 0.2357)

Brokers Members who act as "bridges" connecting different parts of the network.

Node	Degree	Betweenness	Closeness	Eigenvector
1	0.4717	0.1087	0.6543	0.2367
7	0.4717	0.0755	0.6543	0.2433
4	0.3962	0.0725	0.6163	0.1747

Table 7: Broker nodes (Betweenness $\geq$ 0.0670)

Peripheral Members Marginal members with few connections, existing on the network's edges.

Node	Degree	Betweenness	Closeness	Eigenvector
38	0.0377	0.0000	0.4109	0.0256
39	0.0377	0.0000	0.3926	0.0258
40	0.0377	0.0000	0.3557	0.0107
45	0.0377	0.0000	0.4015	0.0164
50	0.0377	0.0000	0.3557	0.0107
53	0.0377	0.0003	0.3681	0.0088

Table 8: Peripheral nodes (Degree $\leq$ 0.0377)

Hierarchy and Vulnerability

These measures test the power structure and resilience of the network.

K-Core Decomposition The most densely connected "core" of the network is identified. The analysis reveals a main core with a **k-value of 11**. This core consists of **13 nodes** (out of 54). The nodes in this core are: `[1, 2, 7, 8, 9, 10, 11, 12, 21, 22, 23, 25, 29]`.

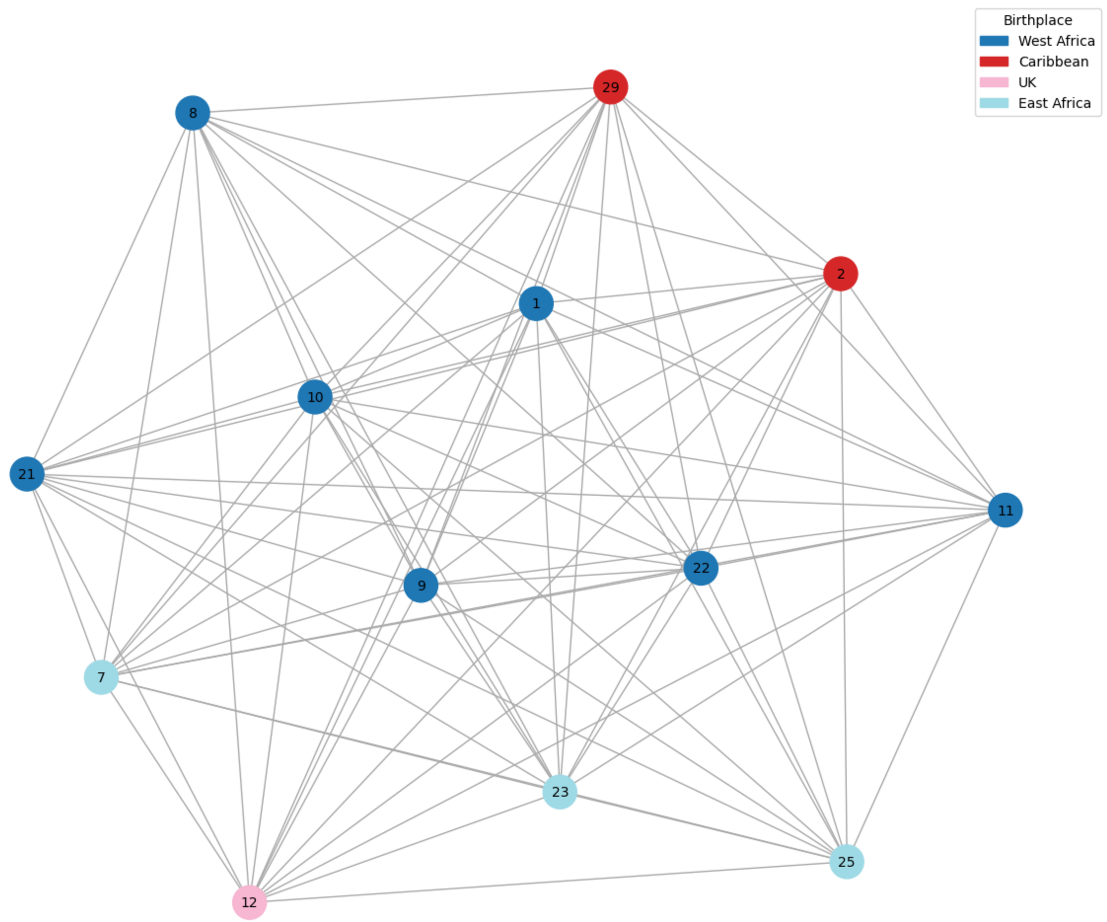


Figure 5: Core of London Network graph visualization.

Vulnerability Simulation We simulated the removal of the identified leaders (Nodes 1, 7, 12), representing a **5.56% reduction in nodes**, and recalculated cohesion metrics. This measure connects roles (leaders) to cohesion (robustness). The results show the network is **extremely robust**: removing the top 3 leaders did not fragment the network (it remained connected). The network density was reduced to **0.1906**, and the average path length increased to **2.2180** (an **8.00%** increase). The high density and clustering create redundancy, making the network resilient to targeted attacks.

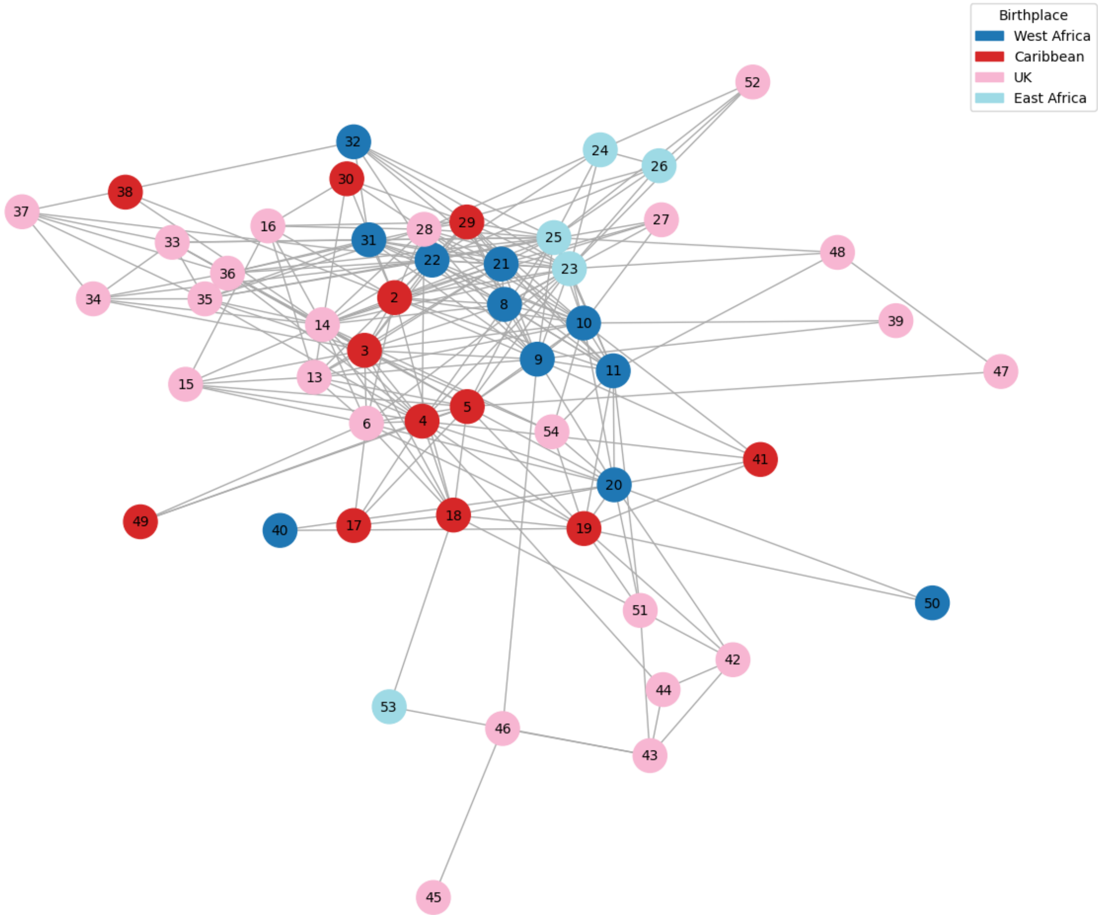


Figure 6: London Network sub-graph visualization without leaders.

Overall, the London network turns out to be a "small-world" (path length 2.05), highly cohesive (density 0.22), locally clustered (clustering 0.63), but undivided (modularity 0.26) network. It possesses a clear hierarchy (k-core 11) and defined social roles (Leaders 1, 7, 12), all of which combine to make it exceptionally **robust**.

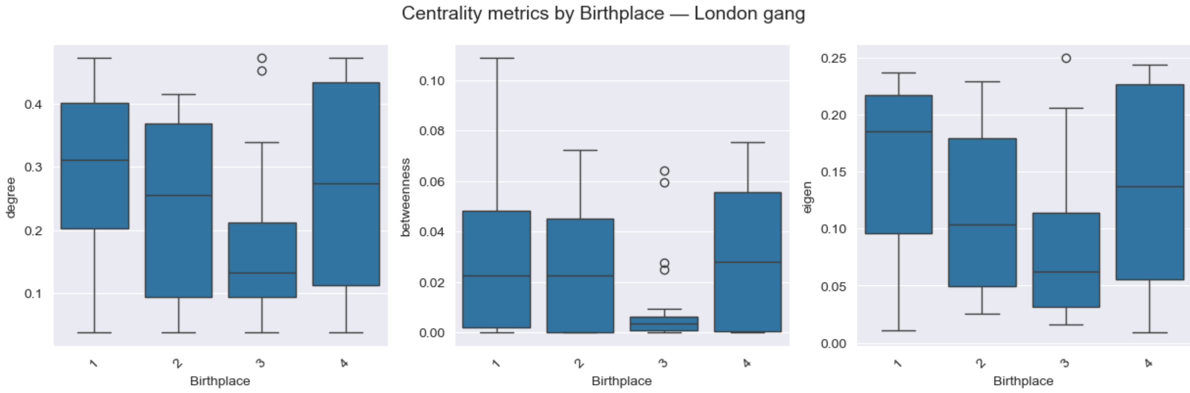
5.2.2 Ethnicity and Community Analysis

The London gang network exhibits a **weak but positive tendency toward ethnic homophily**, reflected by an assortativity coefficient of 0.113. Although individuals show a mild preference for connecting with same-*Birthplace* peers, the network remains largely integrated.
The **mixing matrix** supports this interpretation: diagonal entries (especially for groups 1 and 3) are slightly higher, but substantial off-diagonal values reveal frequent **cross-ethnic connections**.

	1	2	3	4
1	0.111	0.060	0.076	0.041
2	0.060	0.073	0.076	0.025
3	0.076	0.076	0.146	0.043
4	0.041	0.025	0.043	0.025

Table 9: Mixing matrix (proportion of connections between Birthplace groups) – London gang

Regarding **centrality**, groups 1 and 4 emerge as the most structurally prominent, showing the highest degree and eigenvector values (0.286/0.152 and 0.267/0.135). Group 2 follows with intermediate scores, while group 3—despite being the largest—displays the lowest centrality, suggesting a more peripheral or internally clustered role. Overall, influence is distributed across multiple ethnic groups rather than concentrated in one.



The **community analysis** identifies four communities with varying degrees of ethnic diversity. Community 0 shows a balanced mix, while community 1 is dominated by ethnic groups 2 and 3. Communities 2 and 3 are less diverse, particularly community 2, almost entirely composed of group 3 individuals. The mean Shannon index ($H = 0.886$) reflects **moderate diversity** overall.

Community	1	2	3	4
0	0.38	0.10	0.29	0.24
1	0.20	0.35	0.40	0.05
2	0.00	0.14	0.86	0.00
3	0.00	0.33	0.67	0.00

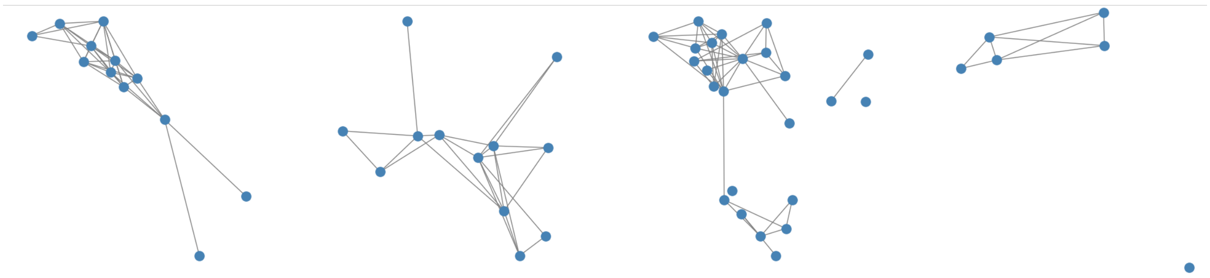
Table 10: Community composition by Birthplace – London gang

A total of 64.44% of edges link individuals from different *Birthplace* groups, indicating **high cross-ethnic integration** and suggesting that national origin is not a primary organizing factor. Subgraph analysis offers further insight:

- Groups **1** and **4** show the strongest internal cohesion (densities 0.530 and 0.533).
- Group **3**, though the largest, has lower internal density (0.167), implying weaker internal connectivity.
- Group **2** displays intermediate cohesion, linking both internally and externally.

Birthplace	Nodes	Edges	Density	Clustering
1	12	35	0.530	0.658
2	12	23	0.348	0.636
3	24	46	0.167	0.506
4	6	8	0.533	0.722

Table 11: Subgraph-level statistics by Birthplace – London gang



In summary, the London gang network presents **moderate ethnic diversity** and **high levels of cross-ethnic integration**. Some Birthplace groups form cohesive internal clusters, but overall the structure remains highly interconnected across ethnic boundaries. Influence is distributed, and ethnicity plays only a limited role in shaping the network's internal organization.

5.3 Comparison of Network Measures

This section presents a comparative analysis of the two covert criminal networks, in which we examine their structural metrics in order to understand the distinct organizational structures of each group.

5.3.1 Structural Comparison

Topology and Cohesion

The structural properties of the two networks reveal markedly different organizational patterns: the Italian Network is considerably sparser than the London one, a difference evident in both its lower **density** (Italian: 0.0516, London: 0.2201) and its smaller **average degree** (Italian: 3.0430, London: 11.67). This suggests that interpersonal ties in the Italian gang are more selectively-distributed, and that interactions are far less intense, while the London gang functions as a highly integrated, tightly-knit community.
Consistently, the Italian network exhibits a longer **average path length** (Italian: 3.012, London: 2.05) and a larger **diameter** (Italian: 6, London: 4), indicating a lower network efficiency. On the other hand, the London Gang constitutes a more structurally efficient environment in which information and communication can propagate more quickly, requiring, on average, only two intermediaries.
Local cohesion reinforces this distinction: the **clustering coefficient** is higher in the the London network (London: 0.6331, Italian: 0.4347), indicating a network that is richer in transitive relationships. The most telling difference in the topology of the networks lies in the community structure. The Italian network displays higher **modularity** (Italian: 0.5561, London: 0.2665), which suggests it is organized into distinct sub-groups or cells. These modules are typically internally cohesive but are only sparsely connected to each other. On the other hand, the the London gang's low modularity, combined with its high density, indicates a lack of significant sub-divisions. It operates as a single, large, cohesive core group rather than a confederation of smaller cells.

Centrality Measures: Hierarchy, Leadership and Brokerage

The analysis of centrality measures of the two networks highlights a clear hierarchical difference. In particular, a clear and steep hierarchy can be observed in the Italian network. The three identified leaders (nodes 19, 63, 18) possess high scores across all centrality measures, while the identified peripheral members are approximately 30 times less central. This aligns with the network's high modularity: these leaders function as **brokers**, bridging the structural holes between the otherwise separated cells.
In the London Gang, the hierarchy appears flatter, as it shows a more balanced distribution of centrality. In particular, two core actors (nodes 1 and 7) occupy both leadership and brokerage positions, but the overall gap between such central nodes and the peripheral ones is smaller—about one order of magnitude.
Furthermore, the identified leaders have high **degree** and **closeness**, but relatively low **betweenness**, which shows they act as "hubs" in the center of a single, dense core, rather than proper brokers connecting disparate groups.

K-Core and Robustness

The K-Core analysis provides an additional insight into the robustness of these two organizations. The Italian network culminates in a modest **3-core** composed of 20 nodes, reinforcing its sparse nature.
As for robustness, removing the identified leaders caused a noticeable increase in average path length and a slight reduction in density, indicating the central role of these individuals in maintaining short communication distances within the core.
On the contrary, the London network exhibits a much more cohesive, robust structure, featuring a **11-core** composed of 13 nodes, which suggests a group with strong internal redundancy and resilience: even after removing key leaders, the network density remains fairily large and the increase in average path length is modest.

5.3.2 Ethnicity Analysis

This section examines how members' ethnicity influences the relational structure of each group, with the aim of discovering to which extent sociocultural factors contribute to the internal functioning of each organization.
While both networks operate in distinct geographical contexts, they share a foundational characteristic: a high degree of integration across ethnic lies. More specifically, the tendency towards ethnic homophily, as measured by the assortativity coefficient, is positive, but remains weak in both cases. The Italian network exhibits a slightly higher coefficient (0.150) compared to the London network (0.113), yet the proximity and the magnitude of the two values indicate that while members may have a slight preference for forming ties with individuals of the same origin, ethnicity harmony is not a dominant structural driver in either case.
This observation is strongly supported by the proportion of cross-ethnic connections. The two networks are remarkably similar in this regard, with 64.91% of ties in the Italian gang and 64.44% of ties in the London gang occurring between individuals of different ethnicity groups. This surprising similarity highlights a common underlying dynamic: both organizations are fundamentally integrated and heavily rely on cross-national cooperation, rather then acting as ethnically segmented groups. The mixing matrices for both networks corroborate these observations: each matrix contains high diagonal values for specific ethnic groups, yet both exhibit non-negligible cross-diagonal values.

Despite this high-level similarity, the two networks exhibit a key difference in their internal community structure, highlighted by the community analysis. In particular, the Italian network, which features a higher Shannon Diversity Index of H = 1.174, demonstrates an overall higher level of internal heterogeneity, meaning that most communities integrate members from multiple birthplaces, with only one (Community 4) being clearly dominated by two ethnic groups.
Conversely, the London Network exhibits lower community diversity, with a Shannon diversity index of H = 0.886, showing that several communities (mainly communities 1, 2 and 3), show strong ethnic concentrations. This pattern indicates that, while cross-ethnic ties remain common at the macroscopic level, the members of this network tend to cluster into ethnically homogeneous groups at the community level.
Concerning the distribution of influence of the different ethnic groups, it can be observed that the Italian network exhibits a relatively concentrated influence structure, with ethnicity group 5 clearly emerging as the most central and influential. In contrast, the London network exhibits a more distributed influence structure, where centrality is not monopolized by a single ethnic group. Instead, it is shared primarily by ethnic groups 1 and 4, with group 2 also playing an important role.

6 Conclusion

Our comparative investigation ultimately reveals two distinct models of covert criminal organizations which, however, share underlying structural patterns and properties.
First, concerning the networks' topologies and their global structural and organizational properties, our analysis demonstrated that the Italian gang operates as a more decentralized, modular organization, characterized by a higher modularity and a steeper hierarchy. On the other hand, the London gang functions as a denser, more cohesive centralized core, with a lower modularity and a flatter leadership structure.
Regarding the influence of ethnicity on tie formation, it emerged from this study that both the analyzed networks demonstrated a fundamental functional reliance on cross-ethnic relationships, evidenced by low ethnic homophily and solid rates of cross-ethnic ties. This suggests that, although existing literature [1] [2] [7] often highlights ethnicity as a major driver for tie formation, individual network instances—such as those examined here—may exhibit different patterns. This does not contradict broader findings, but rather illustrates that complex mechanisms like ethnic homophily may manifest unevenly across contexts.
An important distinction lies in the community structure of the two networks: the Italian network maintains high ethnic diversity within the communities, but presents a single, dominant ethnic group, while the London network, despite its overall integration, internally clusters into more ethnically homogeneous communities.
In conclusion, this analysis highlights that, as regards the examined network instances, ethnicity is not a dominant force able to shape tie formation or dictate interactions in the analyzed networks, but rather interacts complexly with the other network characteristics to shape patterns of cooperation, influence and community organization.

7 Critique

This study effectively provided meaningful insights into both key objectives, successfully outlining the core topological and structural features of both networks, and demonstrating that

ethnicity not always constitutes a unique, monolithic driver for ties between members in the analyzed network.
However, these findings are inevitably constrained by the quality of the data itself. As discussed in the *Validity* section, the datasets represent simplified, static an somehow incomplete models of the real organizations, so the reconstructed topologies are necessarily approximations, especially considering that covert networks are only partially observable. Specifically, the choice to treat both networks as unweighted allowed for an easier comparison, but limited the fidelity of the analysis, since it flattened the distinction between weak interactions and strong ties. In addition, the two datasets differ in the richness and granularity of nodes metadata: the Italian one only provides a country-of-origin variable, while the London dataset contains numerous social and behavioral metadata, which again have been neglected to maintain comparability between networks, in spite of fidelity.
Another limitation arises from the static nature of the model: criminal networks evolve over time, yet the analysis was carried out on a single snapshot for each of the organizations. A temporal analysis could have offered a deeper understanding of the investigated phenomena, if the data had been available.
Despite the discussed limitations, the analysis still offers meaningful insights into the structural characteristics and dynamics of the examined networks, contributing to a clearer understanding on the organizational and interaction patterns of these groups, and providing a useful foundation to future research.

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