Identifying the global terror hubs and vulnerable motifs using complex network dynamics

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ABSTRACT

Terrorism instills fear in the minds of people and takes away the freedom of individuals to act as they will. Terrorism has turned out to be an international menace in the global community; every nation is getting affected, directly or indirectly. Here, we study the terrorist attack incidents which occurred in the last half century across the globe from the open source, Global terrorism database, and develop a view on their spatio-temporal dynamics. We construct a complex network of global terrorism and study its growth dynamics, along with the statistical properties of the network, which are quite intriguing. Normally, each nation pursues its own vision of international security based upon its mandate and particular notions of politics and its policies to counter the threat of terrorism that could naturally include the use of tactical measures and strategic negotiations, or even physical power. We study the resilience of the network against targeted attacks and random failures, which could guide the counter-terrorist outfits in designing strategies to fight terrorism. We then use a disparity filter method to isolate the backbone of the giant component, and identify the terror hubs and vulnerable motifs of global terrorism. We also examine the evolution of the hubs and motifs in a few exemplary cases like Afghanistan, Colombia, Israel, Peru and United Kingdom. The dynamics of the terror hubs and the vulnerable motifs that we discover in the network backbone can provide deep insight on their formations and spreading, and thereby help in contending terrorism or making public policies that can check their spread.

Introduction

Humans are social animals and since the early days of evolution, they have preferred to form and stay together in groups. These groups have evolved from simple settlements to huge nations; defined by multiple causes like language, common heritage, geographical boundaries, and even ideology. The human cooperation has been a motivating force behind the rapid progress of man\textsuperscript{1}. Often evolutionary efforts induced the increase in human cooperation. Various factors, like delayed self-sustenance of young ones, or fear of elimination by neighboring communes competing for similar resources which obstructed the humans to sustain their progeny became reasons for cooperation. This cooperation extended from blood relatives to totally unrelated individuals. Surprisingly, evolution has also been responsible for drawing distinctions among themselves in their bids for survival of the fittest. This segregation\textsuperscript{2,3} can be seen in various forms like race, caste, class, religion, political ideology, etc. Thus, the human social behavior has been extremely convoluted with multiple parameters playing crucial roles. It is extremely difficult to assess the complexity of human social behavior, which has a wide range — co-operations, bonding, conflicts, aggression, coups, wars, etc. Similar to conflicts, aggression and wars, which have plagued mankind from antiquity, acts of terrorism — where a small group of individuals which are similarly motivated in fighting another social institution or organization or exercising indiscriminate violence in achieving financial, political, religious or ideological aim are hardly new. Though there is no single definition, terrorism may be broadly defined as a conscious and deliberate attempt to incite fear among masses through violence or the threat of violence to pursue a political or ideological gain\textsuperscript{4,5}. The aim of terrorism is not limited to eliminating the target group or destruction of opponent’s resources, rather it is specifically carried out to send out a psychological message to the adversary. It is meant to propagate fear among the wider general public which may encompass rival religious or ethnic group, a state government, or an entire country. Terrorists seek to gain leverage they lack on a political scale by changing the scales of power. Even though terrorism has been prevalent ever since modern political landscape has existed, past few decades have seen an exponential increase in terrorist incidents. The scope and nature of terrorist attacks have also evolved rapidly, a fact that became evident to the world on September 11, 2001, when a series of four coordinated attacks were conducted by the Islamic terrorist group al-Qaeda in the United States. Academic and social media reports show an increase in the number of terrorist acts being carried out by an increasing number of terrorist organizations, with extending stretch of the target locations at a global scale. These realities have made it incessantly difficult for counter-terrorist organizations or governments in terminating these terrorist acts.

Apart from solutions by social scientists, physicists have recently tried to provide mathematical models, statistical and network analyses and potential solutions to the menaces of terrorism\textsuperscript{6-8} and conflicts\textsuperscript{9}. Like business conglomerates, terrorist
organizations have also formed transnational ties. They are inter-connected (in a state) and have links with other terrorist organizations outside of the geographical boundaries of the target state.

In this paper, we develop and present a network based study\textsuperscript{10,11} of identification of terrorists and their targets. The international terrorist network is examined and vulnerable motifs of global terrorism network are identified. We analyze the terrorist events from the Global Terrorism database (GTD)\textsuperscript{12,13}, which collected reports from the printed and digital media, over the span of 1970-2016. We construct a complex network of global terrorism and investigate the network characteristics of this anti-social network. We study the resilience of the network against targeted attacks and random failures\textsuperscript{11,14}, which could guide the counter-terrorist outfits in designing strategies to fight terrorism. We also use the disparity filter method\textsuperscript{15} to isolate the backbone of this network, and identify the terror hubs and vulnerable motifs of global terrorism. We then examine the evolution of the hubs and motifs in a few special cases like Afghanistan, Colombia, Israel, Peru and United Kingdom. The backbone evolution and change of relative importance of the terror hubs and the vulnerable motifs are analyzed.

Results

Network construction, structure and backbone

We analyze the terrorist attacks over the entire 46 year period (1970-2016), excluding 1993 (non-availability of data for the given period). In our study, the temporal granularity of the data is one day. Fig. 1 (Top) shows the spatio-temporal distribution of the events across the globe; the dots representing the locations are colored according to different decades during which the events occurred. Evidently, past few decades have seen an exponential increase in terrorist incidents (see Supplementary Information Fig. S7 for the plots attack details and Fig. S8 for the impact of attacks across the globe). Over a period of time \( \tau \), we construct the network of ‘connected’ actors in the following way: Whenever a terrorist source, actor \( a_1 \), attacks a target, actor \( a_2 \), it is recorded as an event \( E_1 \) at time \( t \in [t_0 : t_0 + \tau] \), a directed link ‘connects’ the source to the target by an arrow of unit weight, where \( t_0 \) is the initial time in the entire span \( \tau \). If another event \( E_2 \) within the same time window involves source \( a_3 \) and target \( a_2 \), then \( a_3 \) is connected to \( a_2 \) with a directed link of unit weight. Thus, sources \( a_1 \) and \( a_3 \) are both connected to the common target \( a_2 \). Aggregating all such events over the time window \( \tau \), connected components are formed, as shown in Fig. 1 (Bottom Left). The terrorist network for the entire period consists of 5568 nodes, 64855 edge mentions and 10379 unique edges, with the giant component in grey consisting of 5148 nodes. Thus, the giant component encompasses more than 92\% of the network nodes. The decade-wise evolution of the network along with its giant component is displayed in Fig. S9 of the Supplementary Information.

We extracted (i) the number of mentions \( m \) of each individual actor (source or target) and (ii) the number of co-mentions \( w \) of an unique pair of actors (source-target), as well as the number of unique actors \( k \), one actor is involved with. In terms of the network theory, \( m \) measures node strength, \( w \) the link weight and \( k \) the degree of a node (out-degree for sources and in-degree for targets). While \( m \) and \( k \) measure the importance, activity or visibility of a single actor, \( w \) measures the frequency of involvement of an actor pair (source-target) in the terrorist events. Since this is a directed network, the nodes have distinct out-degree and in-degree distributions.

To find the backbone structure of the weighted network, we have used an algorithm proposed by Serrano et al.\textsuperscript{15}. The disparity filter algorithm extracts the network backbone by considering the relevant edges at all the scales present in the system and by exploiting the local heterogeneity and local correlations among the weights. The disparity filter has a cut-off parameter \( \alpha_c \), the choice of which is arbitrary. It effectively controls the number of nodes and the edges that appear in the backbone. The effect of \( \alpha_c \) on the backbone is displayed in Figure S10 and summarized in Table S2 in Supplementary Information. We have chosen \( \alpha_c = 0.01 \) such that it enables us to follow the country-wise evolution of the terror hubs and vulnerable motifs that appear in the backbone structures. Using the value of the cut-off parameter \( \alpha_c = 0.01 \), we extracted the backbones of the networks for the different periods of evolution. Fig. 1 (Bottom Right) shows the backbone for the network with the aggregated data 1970 to 2016, consisting of 470 nodes (8\% of the total network), 427 edges (4\% of the total network) and 40467 edge mentions (62\% of the total network). The list of names of all the 470 nodes (190 sources and 280 targets) are given in Tables S3-S4 in the Supplementary Information. Fig. 2 shows the growing backbones of the networks for the different decades of evolution. As time evolves the backbone structure grows (number of nodes and edges increase) and becomes more intricate. The number of nodes, unique edges, edge mentions, number of clusters, and the average number of neighbors a node possesses in the growing backbone structures as shown in Fig. 2, are summarized in Table 1. Interestingly, the number of source-target pairs in the backbone structures—indicated by the number of edges, is around 4\% for most years. However, their frequencies of engagement—indicated by the number of edge mentions, grows steadily from 38\% (1970-1980) to 62\% (1970-2016). The average number of neighbors a node possesses, also increases from 1.537 (1970-1980) to 1.817 (1970-2016).

The complementary cumulative probability density function (CCDF) for degree \( Q(k) \) (out- and in-degrees), mentions \( Q(m) \) for sources and targets, and the co-mentions \( Q(w) \) show broad distributions, fitting either power-law, log-normal or stretched exponential distributions (see Fig. 3). The CCDF’s \( Q(s) \) of the cluster size \( s \) for the growing networks are shown in Fig. 3: evidently, the outliers correspond to the sizes of the growing giant cluster (as percentage of the total number of nodes in the
**Figure 1.** *(Top)* Spatio-temporal evolution of attacks for the period 1970 to 2016. The different colored dots indicate the locations of the attacks, along with the years mentioned in the legend. *(Bottom Left)* The aggregated network of terrorism for the period 1970 to 2016 – Network of terrorist attacks constructed from the history of the events. Two types of actors are involved in the network: source and target (source nodes refer to the terrorist organizations and target nodes are the victims). Each actor is a node and whenever two actors are involved in an event, a directed link is drawn from source to target. The network has a giant component (grey) in the center, surrounded by 168 peripheral isolated clusters (black), while the nodes colored in red are showing the backbone; the average degree of a node in the network is 3.718. *(Bottom Right)* The zoomed-in view of the backbone of the network, which has been identified using the disparity filter with $\alpha_c = 0.01$ (see Methods section). The backbone has 470 nodes (190 sources and 280 targets; details summarized in Tables S3-S4 in Supplementary Information) and 427 unique edges.

| Year       | Nodes (%) | Edges (%) | Edge mentions (%) | Number of clusters | Average number of neighbors |
|------------|-----------|-----------|-------------------|--------------------|----------------------------|
| 1970-1980  | 82 (16)   | 63 (3)    | 2490 (38)         | 20                 | 1.537                      |
| 1970-1990  | 179 (17)  | 156 (4)   | 12440 (56)        | 35                 | 1.743                      |
| 1970-2000  | 265 (7)   | 230 (4)   | 17730 (57)        | 51                 | 1.736                      |
| 1970-2010  | 341 (7)   | 308 (4)   | 23707 (57)        | 60                 | 1.806                      |
| 1970-2016  | 470 (8)   | 427 (4)   | 40467 (62)        | 79                 | 1.817                      |
Figure 2. Decade-wise evolution of the network backbone for the period 1970 to 2010 (*Left to Right*). The zoomed-in views of the backbones of the growing network, which have been identified using the disparity filter with $\alpha_c = 0.01$. The characteristics of the growing backbone structure for the different decades, are summarized in Table 1.

network): 1210 (83%) (1970-80), 2346 (88%) (1970-90), 3313 (86%) (1970-2000), 4220 (90%) (1970-2010) and 5148 (92%) (1970-2016). The above results quantitatively characterize the heterogeneity in the activities of the different actors (sources and targets), while most actors are relatively less active. The broad distributions for actor mentions indicate that there are a significant few who constantly engage in terror activities, and that for actor pair mentions indicate similar characteristic for pairs of source-target (see Table S5 in Supplementary Information for the list of top-50 actor pairs– source-target). The broad degree distributions indicate that the number of actors engaging with very large number of actors are also quite significant; the form of the distribution shows little change. Notably, the average clustering coefficient of the nodes in the backbone is zero (indicating the absence of loops), contrary to most social networks of friendships, collaborations, etc., where typically the average clustering coefficient is high$^{10,11}$.

**Tolerance of network to attack and failure**

We study how the network breaks down under attack, in order to stop terrorism activities to happen$^{14}$. The largest connected component of the network (i.e., the giant component) is subjected to targeted attack by removal of the most connected nodes (in terms of the source out-degree, which corresponds to a terrorist organization, etc.). As the network is directed, so we started by removing the source node with the highest out-degree, followed by the next highest out-degree and so on. This results in rapid fragmentation or destruction of the network by removing all the source nodes/negative nodes. We compute the fraction of nodes $GC$ present in the largest cluster, which is observed to decrease very quickly, and the average number of nodes in the isolated clusters other than the giant component $\langle ac \rangle$, with increasing fraction of removed nodes. The network and the giant component are destroyed faster by targeted nodes removal (attack), compared to the random node removal (failure), as shown in Fig. 4.

**Evolution of the hubs and motifs in the backbone structure**

Using the disparity filter method, we isolate the backbone of this network and identify the terror hubs and vulnerable motifs of global terrorism. As obvious, all the terror hubs and vulnerable motifs that are very frequently engaged appear in the backbone. We show in Fig. 5, the evolution of the hubs and motifs in a few exemplary cases like Afghanistan (AFG), Colombia (COL), Israel (ISR), Peru (PER) and United Kingdom (GBR). The very fact that the backbone structure evolves indicates that often some terrorist organizations gain more prominence than others. Examining these hubs and motifs, we observe that the *star-structure* occurs quite frequently in the backbone: one source attacking many targets, or one target being attacked by many sources. The backbone structure of ISR grows from a simple structure of three nodes (1 source and 2 targets; average degree 1.33) in 1970-1980, to an intricate structure of twenty nodes (14 sources and 6 targets; average degree 1.90) in 1970-2016. The backbone structure of GBR remains fairly the same; the average degree grows from 1.85 (1970-1980) to 1.91 (1970-2016); the Irish Republican Army is the main terrorist hub, while the private citizens and property is the most vulnerable target for the entire duration. In COL, the backbone structure grows from a simple 3 node (1 source and 2 targets) in 1970-1980 to a clustered 11 nodes (5 sources and 6 targets) in 1970-1990; the average degree jumps from 1.33 to 2.91. Then it grows steadily to a closely knit structure of 15 nodes (6 sources and 9 targets) at the end of 2016. Interestingly, AFG does not appear in the backbone till the 2000-2010, and government (Diplomatic) GOVD_USA is a common target which links two countries AFG and PER. This is typically the case in many other empirical networks, where there exists a node connecting two modules or communities$^{16}$. In AFG and PER, we again see the appearance of star structures, as in GBR. We have also observed in Fig. 2
Figure 3. The complementary cumulative probability density functions (CCDF’s) for the decade-wise data: (Top Left and Right) In-degrees and out-degrees (Middle Left and Right) Actor Mentions (outgoing for sources and incoming targets), (Bottom Left) Co-actor Mentions and (Bottom Right) Cluster size distribution, with the giant clusters as outliers.
Figure 4. (Top) The structure of network (directed) under targeted attack: Terrorist source nodes are removed in the sequence of their out-degree starting from the highest out-degree. The plots shows the behavior of the giant component $GC$ (fraction of nodes in the largest connected component) and the average number of nodes in the isolated clusters other than the giant component $\langle ac \rangle$, with increasing fraction of removed nodes. (Bottom) The structure of network (directed) under random failure: Nodes having out-degree are removed randomly. The network and the giant component are destroyed faster by targeted nodes removal (attack), compared to the random node removal (failure): $GC$ becomes zero after about 33% of the sources are removed through the former method, and about 87% of the sources are removed through the latter. The results are shown for the network aggregated over 1970 – 2016.
Figure 5. Growth of the backbones for the decades 1970 to 2016 (Left to Right), in the countries: (Top to Bottom) Israel (ISR), United Kingdom (GBR), Columbia (COL), Afghanistan (AFG) and Peru (PER). The zoomed-in views of the backbones of the network, which have been identified using the disparity filter with $\alpha_c = 0.01$.

that El Salvador (SLV) had appeared in 1970-1980 and 1970-1990 backbones, but does not appear since then; this conforms to the fact that Chapultepec peace accords were signed in 1992.

These observations on the dynamics of the terror hubs and the vulnerable motifs in the network backbone that we highlighted above, can provide deep insight on their formations and spreading, and thereby help in contending terrorism or making public policies that can reduce their spread. Our results for the range of provided parameters describe the evolution of terrorism in the above countries that emerge from the network analysis. The results are in no way a comment on the previous policies of the Governments of the countries considered.

Discussions

We have examined the spatio-temporal dynamics of the terrorist events across the globe, using the Global Terrorism database (GTD)\textsuperscript{12,13} over the span of 46 years from 1970 to 2016. We developed the view of a complex network of global terrorism and studied its growth dynamics along with the statistical regularities of the network properties. The statistical properties of the network are quite interesting and robust. The network always has a giant component, which is about 83\% to 92\% of the total number of nodes in the network. The complementary cumulative probability density functions for the degrees ($k$), mentions ($m$), and source-target mentions ($w$) are broad (power laws, log-normals or stretched exponentials). We studied the resilience of the network against targeted attacks and random failures. The giant component disappears after about 33\% of the hubs (in descending order of magnitude) are removed; in the case of random removal of sources, the giant component disappears much slower— only after 87\% of the sources are removed. We isolated the backbone of the terrorist network using the disparity filter method, and identified the terror hubs and vulnerable motifs of global terrorism. The backbones for the various decades contain between 8\% to 16\% of the total number of the nodes; the number of unique edges remain fairly constant around 4\% of the total number of edges in the network. Most importantly, the edge mentions grow from 38\% to 62\% of the total network, signifying very high frequency of engagement between a small number of source-target pairs. The terror hubs and vulnerable motifs are
seen to have star structures more frequently than by chance. The average degree of a node in the backbone increases steadily as time evolves. The average clustering coefficient is always observed to be zero (indicating the absence of triangles) in the growing network, as well as the evolving backbone. We analyzed the evolutionary structures of the hubs and motifs in a few special cases like Afghanistan, Colombia, Israel, Peru and United Kingdom. We also observed that US citizens, businessmen, and other organizations are often the common target nodes linking different closed knit communities of terrorist organizations from other countries. The observation that El Salvador appeared only in the backbones of 1970 – 1980 and 1970 – 1990 and not thereafter, conforming to the fact that Chapultepec peace accords were signed in 1992, is a significant outcome of the network backbone analysis.

The political and socioeconomic conditions along with the local circumstances of a region, play key roles in framing anti-terrorism policies and elimination of terrorist ties. The inter-disciplinary approaches of network analysis that we have used in this paper, may provide supplementary knowledge and insight on the formation and spreading of terrorism, and thereby help the international security agencies in contending terrorism, as well as produce acumen for the policy makers and experts of international relations.

Materials and Methods

Data description and filtration
The source for this analysis is open-access data\textsuperscript{12,13} generously provided by the National Consortium for the Study of Terrorism and Responses to Terrorism (START), University of Maryland. The data provides a detailed account of terrorist events from 1970 to 2016, except for year 1993 for which no data existed. The dataset has 170350 instances divided into 135 attributes. The dataset required considerable cleaning before any study could be done. The doubtful events, suggested by dataset itself, were removed. Further, attacks carried out by ‘Unknown’ terrorist organization on ‘Unknown’ targets were also filtered out. The events which had no spatial information in the dataset were removed, too. To maintain the network modularity at country level any attack which targeted international community instead of a particular nationality was also removed from the dataset. The feature selection consisted of removing explanatory attributes of the dataset. The cleaning left us with 64980 instances of 11 attributes (see Fig. S6 in Supplementary Information).

Disparity filter to identify backbone
To find the backbone structure of a weighted network, we have used the algorithm proposed by Serrano et al.\textsuperscript{15}. The disparity filter algorithm extracts the network backbone by considering the relevant edges at all the scales present in the system and exploiting the local heterogeneity and local correlations among the weights. The disparity filter has a cut-off parameter $\alpha_c$, which determines the number of edges that are reduced in the original network. The filter however, preserves the cutoff of the degree distribution, the form of the weight distribution, and the clustering coefficient.

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Author contributions statement

K.S. and A.C. designed research; S.S.H., K.S., V.K., and A.C. performed research; S.S.H., K.S. and V.K. processed and analyzed data; K.S. and V.K. prepared all the figures, and K.S., V.K. and A.C. wrote the manuscript.

Supplementary information

Data

The data source utilized for this quantitative analysis of terrorism is obtained from the Global Terrorism Database (GTD), maintained by the National Consortium for the Study of Terrorism and Responses to Terrorism (START) at the University of Maryland, United States. The database was built on unclassified source material publicly available in media, digital news archives, books, journals, and some legal documents. GTD contains 170350 terrorist events reported for a period of 46 years from 1970 to 2016. The events of 1993 are not present in the database as they were lost prior to START’s compilation. The dataset includes 135 variables such as GTD Id, date of incident, incident location, incident information, attack information, target/victim information, perpetrator information, perpetrator statistics, claims of responsibility, weapon information, casualty information, consequences, kidnapping/hostage taking information, additional information, and source information. A snapshot of few variables is shown in Figure 6.

Figure 6. Snapshot displaying few representative columns of the dataset.
Terrorist attacks

Different statistics and details of the terrorist attacks from 1970-2016, are shown in Figure S7.

Figure 7. (Top) Year-wise count of terror activities. Note that no data was available for the year 1993. (Middle Left) Heatmap of the event count of global terrorism, showing the intensity and distribution. (Middle Right) Count of terror activities in the top-10 affected countries. (Bottom Left) Target types—most frequent targets of terrorists, and (Bottom Right) Attack types—favorite modus operandi for assaults. All results are for the period 1970-2016.

Fatalities vs. injured

The impact of the terrorist attacks, as given by the number of persons killed or wounded, are shown in Figure S8. Interestingly, they have broad distributions.
Figure 8. The complementary cumulative probability density function (CCDF) for: (Left) The number of total confirmed fatalities for the incidents along with the perpetrator fatalities. The number includes all victims and attackers who died as a direct result of the incident. (Right) The number of confirmed non-fatal injuries to both perpetrators and victims along with the number of perpetrator fatalities. All results are for the period 1970-2016.

Evolution of Network and Giant Component
Decade-wise evolution of the network and its giant component is shown in Figure S9.

Figure 9. Decade-wise evolution of the network and its giant component (From left to right). The network consists of 1459 nodes in 1970-1980, 2658 nodes in 1970-1990, 3832 nodes in 1970-2000, 4669 nodes in 1970-2010, and 5568 nodes in 1970-2016. The size of the Giant Component (shown in red) and its percentage size with respect to the entire network is 1210 (83%) in 1970-80, 2346 (88%) in 1970-90, 3313 (86%) in 1970-00, 4220 (90%) in 1970-10, and 5148 (92%) in 1970-2016.
Effect of the disparity filter cut-off $\alpha_c$ on the backbone

The comparison of backbone characteristics (as percentage figures of the total weights $\%W_T$ of the network, total nodes $\%N_T$ in the network and total unique edges $\%E_T$ in the network) with the change in disparity filter cut-off $\alpha_c$, for the different evolving backbones for the period 1970-2016, is summarized in Table S2.

| Year     | $\alpha_c$ | $\%W_T$ | $\%N_T$ | $\%E_T$ |
|----------|------------|---------|---------|---------|
| 1970-1980| 0.05       | 48      | 9       | 6       |
|          | 0.04       | 45      | 9       | 5       |
|          | 0.03       | 43      | 8       | 4       |
|          | 0.02       | 40      | 7       | 4       |
|          | 0.01       | 38      | 6       | 3       |
| 1970-1990| 0.05       | 65      | 11      | 7       |
|          | 0.04       | 64      | 10      | 6       |
|          | 0.03       | 62      | 10      | 5       |
|          | 0.02       | 60      | 8       | 5       |
|          | 0.01       | 56      | 7       | 4       |
| 1970-2000| 0.05       | 65      | 11      | 6       |
|          | 0.04       | 64      | 10      | 6       |
|          | 0.03       | 63      | 9       | 5       |
|          | 0.02       | 61      | 8       | 5       |
|          | 0.01       | 57      | 7       | 4       |
| 1970-2010| 0.05       | 65      | 12      | 7       |
|          | 0.04       | 64      | 11      | 6       |
|          | 0.03       | 63      | 10      | 5       |
|          | 0.02       | 60      | 9       | 5       |
|          | 0.01       | 57      | 7       | 4       |
| 1970-2016| 0.05       | 70      | 13      | 7       |
|          | 0.04       | 68      | 12      | 6       |
|          | 0.03       | 67      | 11      | 6       |
|          | 0.02       | 65      | 10      | 5       |
|          | 0.01       | 62      | 8       | 4       |

Table 2. Comparison of backbone characteristics (as percentage figures of the total weights $\%W_T$ of the network, total nodes $\%N_T$ in the network and total unique edges $\%E_T$ in the network) with the change in disparity filter cut-off $\alpha_c$, for the different evolving backbones.
The backbone structures are displayed in the Figure S10.

Figure 10. Effect of $\alpha_c$ on the evolving backbones. *(From Left to Right)* Different values of $\alpha_c = 0.02, 0.03, 0.04, 0.05$).
*(From Top to Bottom)* Different decades 1970-1980, 1970-1990, 1970-2000, 1970-2010 and 1970-2016, respectively.
Lists of names of sources, targets and actor pairs
The names of 190 sources and their abbreviations that appear in the backbone of the global terrorist network with 470 nodes are given in Table S3.

| Sr. No. | Source Name                                      | Source Abbreviation |
|---------|--------------------------------------------------|---------------------|
| 1       | 23rd of September Communist League_Mexico       | 23SepCL_MEX         |
| 2       | 31 January People’s Front (FP-31)_Guatemala      | FP-31_GTM           |
| 3       | Abu Sayyaf Group (ASG)_Philippines              | ASG_PHL             |
| 4       | Action Directe_France                           | AcDir_FRA           |
| 5       | African National Congress (South Africa)_South Africa | ANC_ZAF     |
| 6       | Aynad Misr_Egypt                                | AjM_EGY             |
| 7       | Al-Aqsa Martyrs Brigade_Israel                  | AQM_ISR             |
| 8       | Al-Aqsa Martyrs Brigade_West Bank and Gaza Strip | AQM_WBGS            |
| 9       | Al-Fatah_West Bank and Gaza Strip               | Al-Fatah_WBGS       |
| 10      | Al-Gama’at al-Islamiyya (IG)_Egypt              | IG_EGY              |
| 11      | Algerian Islamic Extremists_Algieria            | DZA_IE_DZA          |
| 12      | Allied Democratic Forces (ADF)_Democratic Republic of the Congo | ADF_COD |
| 13      | Al-Nusra Front_Syria                            | ANF_SYR             |
| 14      | Al-Qaida in Iraq_Iraq                           | AQIIRQ              |
| 15      | Al-Qaida in the Arabian Peninsula (AQAP)_Yemen   | AQAP_YEM            |
| 16      | Al-Qaida in the Islamic Maghreb (AQIM)_Algeria   | AQIM_DZA            |
| 17      | Al-Shabaab_Kenya                                | ASB_KEN             |
| 18      | Al-Shabaab_Somalia                              | ASB_SOM             |
| 19      | Anarchists_Greece                               | ANR_GRC             |
| 20      | Animal Liberation Front (ALF)_United States     | ALF_USA             |
| 21      | Ansar al-Sharia (Libya)_Libya                   | AASL_LBY            |
| 22      | Anti-Abortion extremists_United States          | AAE_USA             |
| 23      | Anti-Balaka Militia_Central African Republic    | ABM_CAF             |
| 24      | Arab Separatists_Iran                           | ArbSEP_IRN          |
| 25      | Armed Forces of National Resistance (FARN)_El Salvador | FARN_SLV |
| 26      | Armed Islamic Group (GIA)_Algeria               | GIA_DZA             |
| 27      | Armed Revolutionary Independence Movement (MIRA)_United States | MIRA_USA |
| 28      | Army of God_United States                       | ArGod_USA           |
| 29      | Asa’ib Ahl al-Haqiq_Iraq                        | AAH_IRQ             |
| 30      | Baader-Meinhof Group_Ireland                    | BMG_ITA             |
| 31      | Baader-Meinhof Group_West Germany (FRG)         | BMG_WestDEU(FRG)    |
| 32      | Baloch Liberation Front (BLF)_Pakistan          | BLF_PAK             |
| 33      | Baloch Republican Army (BRA)_Pakistan           | BRA_PAK             |
| 34      | Barqa Province of the Islamic State_Libya       | BARIS_LBY           |
| 35      | Basque Fatherland and Freedom (ETA)_Spain       | ETA_ESP             |
| 36      | Black Nationalists_United States                | BN_USA              |
| 37      | Black Panthers_United States                    | BP_USA              |
| 38      | Boko Haram_Cameroon                             | BH_CMR              |
| 39      | Boko Haram_Chad                                 | BH_TCD              |
| 40      | Boko Haram_Niger                                | BH_NER              |
| 41      | Boko Haram_Nigeria                              | BH_NGA              |
| 42      | Chechen Rebels_Russia                           | ChReb_RUS           |
| 43      | Chukakuha (Middle Core Faction)_Japan           | ChukakuhaMCF_JPN    |
| 44      | Communist Party of India - Maoist (CPI-Maoist)_India | CPI-Maoist_IND |
| 45      | Communist Party of Nepal-Maoist (Baidya)_Nepal  | CPNPL-Maoist_NPL    |
| 46      | Communists_Philippines                          | Communists_PHL      |
| 47      | Conspiracy of Cells of Fire_Greece              | CCF_GRC             |
| 48      | Coordination Committee (CORCOM)_India           | CORCOM_IND          |
| 49      | Corsican National Liberation Front (FLNC)_France | FLNC_FRA           |
|   |                                                                                     |                     |
|---|-------------------------------------------------------------------------------------|---------------------|
|50 | Corsican National Liberation Front- Historic Channel, France                        | CNLF-HC_FRA         |
|51 | Death Squad, El Salvador                                                           | DS_SLV              |
|52 | Death Squad, Guatemala                                                            | DS_GTM              |
|53 | Democratic Front for the Liberation of Rwanda (FDLR), Democratic Republic of the Congo | FDLR_COD            |
|54 | Dev Sol, Turkey                                                                  | DevSol_TUR          |
|55 | Dissident Republicans, United Kingdom                                             | DisRep_GBR          |
|56 | Donetsk People’s Republic, Ukraine                                               | DPR_UKR             |
|57 | Earth Liberation Front (ELF), United States                                       | ELF_USA             |
|58 | Ejercito Revolucionaria del Pueblo (ERP), (Argentina), Argentina                   | ERP(ARG)_ARG        |
|59 | Farabundo Marti National Liberation Front (FMLN), El Salvador                      | FMLN_SLV            |
|60 | Fighting Proletarian Squads, Italy                                                | FFS_ITA             |
|61 | First of October Antifascist Resistance Group (GRAPO), Spain                      | GRAPO_ESP           |
|62 | Free Aceh Movement (GAM), Indonesia                                               | FrAc(GAM)_IDN       |
|63 | Free Syrian Army, Syria                                                           | FSA_SYR             |
|64 | Fuerzas Armadas de Liberacion Nacional (FALN), United States                      | FALN_USA            |
|65 | Fulani extremists, Nigeria                                                        | FE_NGA              |
|66 | Guerrilla Army of the Poor (EGP), Guatemala                                       | GAP(EGP)_GTM        |
|67 | Hamas (Islamic Resistance Movement), Israel                                        | Hamas_ISR           |
|68 | Hamas (Islamic Resistance Movement), West Bank and Gaza Strip                      | Hamas_WBGs          |
|69 | Haqqani Network, Afghanistan                                                      | HQN_AFG             |
|70 | Hezbollah, Israel                                                                | Hez_ISR             |
|71 | Hezbollah, Lebanon                                                                | Hez_LBN             |
|72 | Houthi extremists (Ansar Allah), Saudi Arabia                                     | Houthi_SAU          |
|73 | Houthi extremists (Ansar Allah), Yemen                                            | Houthi_YEM          |
|74 | Hutu extremists, Burundi                                                          | Hutuextremists_BDI  |
|75 | Institutional Revolutionary Party (PRI), Mexico                                   | PRI_MEX             |
|76 | Irish Republican Army (IRA), Ireland                                             | IRA_JRL             |
|77 | Irish Republican Army (IRA), United Kingdom                                       | IRA_GBR             |
|78 | Irish Republican Extremists, United Kingdom                                       | IRE_GBR             |
|79 | Islamic Front (Syria), Syria                                                      | IF(SYR)_SYR         |
|80 | Islamic Salvation Front (FIS), Algeria                                            | FIS_DZA             |
|81 | Islamic State of Iraq and the Levant (ISIL), Iraq                                 | ISIL_IRQ            |
|82 | Islamic State of Iraq and the Levant (ISIL), Lebanon                              | ISIL_LBN            |
|83 | Islamic State of Iraq and the Levant (ISIL), Syria                                | ISIL_SYR            |
|84 | Islamic State of Iraq and the Levant (ISIL), Turkey                               | ISIL_TUR            |
|85 | Islamic State of Iraq and the Levant (ISIL), Turkey                               | ISIL_TUR            |
|86 | Israeli extremists, West Bank and Gaza Strip                                      | ISRelex_WBGs        |
|87 | Israeli settlers, West Bank and Gaza Strip                                        | ISRelsetters_WBGs   |
|88 | Jamaat-E-Islami, Bangladesh                                                       | JEIs(BGD)_BGD       |
|89 | Janatantrik Terai Mukti Morcha, Jwala Singh (JTMM-J), Nepal                       | JTMM-J_NPL          |
|90 | Janjaweed, Sudan                                                                 | JNJD_SDN            |
|91 | Jemaah Islamiya (JI), Indonesia                                                   | JLJDN               |
|92 | Jewish Defense League (JDL), United States                                       | JDL_USA             |
|93 | Karen National Union, Myanmar                                                     | KNU_MMR             |
|94 | Khmer Rouge, Cambodia                                                             | KhRo_KHM            |
|95 | Khorasan Chapter of the Islamic State, Pakistan                                   | KHCI_PAK            |
|96 | Kurdistan Workers’ Party (PKK), Germany                                           | KWP(PKK)_DEU        |
|97 | Kurdistan Workers’ Party (PKK), Turkey                                            | KWP(PKK)_TUR        |
|98 | Lashkar-e-Jhangvi, Pakistan                                                       | LeJ_PAK             |
|99 | Left-Wing Militants, United States                                               | LWM_USA             |
|100| Liberation Tigers of Tamil Eelam (LTTE), Sri Lanka                                | LTTE_LKA            |
| 102 | Lord’s Resistance Army (LRA), Democratic Republic of the Congo | LRA_COD |
| 103 | Lord’s Resistance Army (LRA), Sudan | LRA_SDN |
| 104 | Lord’s Resistance Army (LRA), Uganda | LRA_UGA |
| 105 | Loyalists, United Kingdom | LYL_GBR |
| 106 | Luhansk People’s Republic, Ukraine | LPR_UKR |
| 107 | M-19 (Movement of April 19), Colombia | M-19_COL |
| 108 | Mahdi Army, Iraq | MAIRQ |
| 109 | Manuel Rodriguez Patriotic Front (FPMR), Chile | FPMR_CHL |
| 110 | Maoists, India | Maoists_IND |
| 111 | Maoists, Nepal | Maoists_NPL |
| 112 | Mayi Mayi, Democratic Republic of the Congo | MayiMayi_COD |
| 113 | Meibion Glyndwr, United Kingdom | McGlyn_GBR |
| 114 | Monteros (Argentina), Argentina | Mont(ARG)_ARG |
| 115 | Moro Islamic Liberation Front (MILF), Philippines | MILF_PHL |
| 116 | Moro National Liberation Front (MNLF), Philippines | MNLF_PHL |
| 117 | Movement of the Revolutionary Left (MIR) (Chile), Chile | MIR(CHL)_CHL |
| 118 | Mozambique National Resistance Movement (MNR), Mozambique | MNR MOZ |
| 119 | Mujahedin-e Khalq (MEK), Iran | MEK_IRN |
| 120 | Murle Tribe, Ethiopia | MT_ETH |
| 121 | Muslim extremists, Libya | ME_LBY |
| 122 | Muslim extremists, Syria | ME_SYR |
| 123 | Muslim Rebels, Algeria | MR_DZA |
| 124 | Muttahida Qami Movement (MQM), Pakistan | MQM_PAK |
| 125 | National Democratic Front of Bodoland (NDFB), India | NDFB_IND |
| 126 | National Liberation Army (NLA) (Macedonia), Macedonia | NLA(MKD)_MKD |
| 127 | National Liberation Army of Colombia (ELN), Colombia | ELN_COL |
| 128 | National Liberation Front of Tripura (NLFT), India | NLFT_IND |
| 129 | National Socialist Council of Nagaland-Isak-Muivah (NSCN-IM), India | NSCN-IM_IND |
| 130 | National Union for the Total Independence of Angola (UNITA), Angola | UNITA_AGO |
| 131 | National Union for the Total Independence of Angola (UNITA), Namibia | UNITA_NAM |
| 132 | National Union for the Total Independence of Angola (UNITA), Zambia | UNITA_ZMB |
| 133 | New People’s Army (NPA), Philippines | NPA_PHL |
| 134 | New World Liberation Front (NWLF), United States | NWLF_USA |
| 135 | Nicaraguan Democratic Force (FDN), Nicaragua | FDN_NIC |
| 136 | Niger Delta Avengers (NDA), Nigeria | NDA_NGA |
| 137 | November 17 Revolutionary Organization (N17RO), Greece | N17RO_GRC |
| 138 | Omega-7, United States | OMG_USA |
| 139 | Opposition Group, Bangladesh | OG_BGD |
| 140 | Palestinian Extremists, Israel | PE_ISR |
| 141 | Palestinian Extremists, West Bank and Gaza Strip | PE_WBGS |
| 142 | Palestinian Islamic Jihad (PIJ), Israel | PIJ_ISR |
| 143 | Palestinians, Israel | Pls_ISR |
| 144 | Palestinians, West Bank and Gaza Strip | Pls_WBGS |
| 145 | Patriotic Morazanista Front (FPM), Honduras | FPM_HND |
| 146 | Patriotic Resistance Front in Ituri (FRPI), Democratic Republic of the Congo | FRPI_COD |
| 147 | People’s Liberation Forces (FPL), El Salvador | FPL_SLV |
| 148 | People’s Liberation Front (JVP), Sri Lanka | JVP_LKA |
| 149 | Popular Front for the Liberation of Palestine (PFLP), Israel | PFLP_ISR |
| 150 | Popular Liberation Army (EPL), Colombia | EPL_COL |
| 151 | Popular Resistance Committees, Israel | PRC_ISR |
| 152 | Popular Revolutionary Bloc (BPR), El Salvador | BPR_SLV |
| 153 | Prima Linea, Italy | PrimaLinea_ITA |
Table 3. Names and abbreviations of Sources that appear in the backbone structure (1970-2016).

The names of 280 targets and their abbreviations that appear in the backbone of the global terrorist network with 470 nodes are given in Table S4.

| Sr. No. | Target Name                                                   | Target     |
|---------|--------------------------------------------------------------|------------|
| 1       | Government (General),Afghanistan                             | GOVG_AFG   |
| 2       | Police,Afghanistan                                          | POL_AFG    |
| 3       | Private Citizens & Property,Afghanistan                      | PCP_AFG    |
| 4       | Police,Algeria                                              | POL_DZA    |
| 5       | Business,United States                                      | BUS_USA    |
| 6       | Private Citizens & Property,Burundi                         | PCP_BDI    |
| 7       | Private Citizens & Property,Democratic Republic of the Congo | PCP_COD    |
| 8       | Police,Egypt                                                | POL_EGY    |
| 9       | Police,India                                                | POL_IND    |
| No. | Category                                      | Country         | Code |
|-----|----------------------------------------------|-----------------|------|
| 10  | Private Citizens & Property                   | India           | PCP_IND |
| 11  | Police                                       | Iraq            | POL_IRQ |
| 12  | Private Citizens & Property                   | Iraq            | PCP_IRQ |
| 13  | Business                                     | Iraq            | BUS_IRQ |
| 14  | Police                                       | Kenya           | POL_KEN |
| 15  | Private Citizens & Property                   | Libya           | PCP_LBY |
| 16  | Private Citizens & Property                   | Cameroon        | PCP_CMR |
| 17  | Private Citizens & Property                   | Nigeria         | PCP_NGA |
| 18  | Educational Institution                      | Pakistan        | EDI_PAK |
| 19  | Police                                       | Pakistan        | POL_PAK |
| 20  | Private Citizens & Property                   | Pakistan        | PCP_PAK |
| 21  | Business                                     | Philippines     | BUS_PHL |
| 22  | Government (General)                         | Philippines     | GOVG_PHL |
| 23  | Private Citizens & Property                   | Philippines     | PCP_PHL |
| 24  | Government (General)                         | Somalia         | GOVG_SOM |
| 25  | Private Citizens & Property                   | Somalia         | PCP_SOM |
| 26  | Private Citizens & Property                   | South Sudan     | PCP_SouthSDN |
| 27  | Private Citizens & Property                   | Sudan           | PCP_SDN |
| 28  | Private Citizens & Property                   | Uganda          | PCP_UGA |
| 29  | Private Citizens & Property                   | Syria           | PCP_SYR |
| 30  | Private Citizens & Property                   | Turkey          | PCP_TUR |
| 31  | Police                                       | Turkey          | POL_TUR |
| 32  | Private Citizens & Property                   | Ukraine         | PCP_UKR |
| 33  | Police                                       | United States   | POL_USA |
| 34  | Police                                       | Israel          | POL_ISR |
| 35  | Private Citizens & Property                   | Israel          | PCP_ISR |
| 36  | Private Citizens & Property                   | West Bank and Gaza Strip | PCP_WBGS |
| 37  | Government (General)                         | Yemen           | GOVG_YEM |
| 38  | Police                                       | Yemen           | POL_YEM |
| 39  | Private Citizens & Property                   | Yemen           | PCP_YEM |
| 40  | Private Citizens & Property                   | Northern Ireland | PCP_NIRL |
| 41  | Abortion Related                             | United States   | Abor_USA |
| 42  | Private Citizens & Property                   | United States   | PCP_USA |
| 43  | Private Citizens & Property                   | Angola          | PCP_AGO |
| 44  | Utilities                                    | Angola          | UTL_AGO |
| 45  | Business                                     | Great Britain   | BUS_GBR |
| 46  | Business                                     | Northern Ireland | BUS_NIRL |
| 47  | Police                                       | Northern Ireland | POL_NIRL |
| 48  | Utilities                                    | Chile           | UTL_CHL |
| 49  | Transportation                               | China           | TRP_CHN |
| 50  | Business                                     | Colombia        | BUS_COL |
| 51  | Police                                       | Colombia        | POL_COL |
| 52  | Private Citizens & Property                   | Colombia        | PCP_COL |
| 53  | Transportation                               | Colombia        | TRP_COL |
| 54  | Government (General)                         | Colombia        | GOVG_COL |
| 55  | Utilities                                    | Colombia        | UTL_COL |
| 56  | Business                                     | Peru            | BUS_PER |
| 57  | Government (General)                         | Peru            | GOVG_PER |
| 58  | Private Citizens & Property                   | El Salvador     | PCP_SLV |
| 59  | Utilities                                    | El Salvador     | UTL_SLV |
| 60  | Government (General)                         | El Salvador     | GOVG_SLV |
| 61  | Business                                     | France          | BUS_FRA |
| No. | Category                                      | Country          | Code |
|-----|----------------------------------------------|------------------|------|
| 62  | Private Citizens & Property                  | Algeria          | PCP   |
| 63  | Government (General)                         | France           | GOVG  |
| 64  | Police                                       | Spain            | POL   |
| 65  | Military                                     | United States    | MIL   |
| 66  | Private Citizens & Property                  | Guatemala        | PCP   |
| 67  | Government (General)                         | Iran             | GOVG  |
| 68  | Business                                     | Ireland          | BUS   |
| 69  | Business                                     | Turkey           | BUS   |
| 70  | Terrorists/Non-State Militia                 | Lebanon          | TNSM  |
| 71  | Private Citizens & Property                  | Mozambique       | PCP   |
| 72  | Transportation                               | Mozambique       | TRP   |
| 73  | Government (General)                         | Nepal            | GOVG  |
| 74  | Utilities                                    | Pakistan         | UTL   |
| 75  | Police                                       | Peru             | POL   |
| 76  | Private Citizens & Property                  | Peru             | PCP   |
| 77  | Utilities                                    | Peru             | UTL   |
| 78  | Police                                       | Philippines      | POL   |
| 79  | Private Citizens & Property                  | Saudi Arabia     | PCP   |
| 80  | Government (General)                         | South Africa     | GOVG  |
| 81  | Police                                       | South Africa     | POL   |
| 82  | Government (General)                         | Soviet Union     | GOVD  |
| 83  | Business                                    | Spain            | BUS   |
| 84  | Government (General)                         | Spain            | GOVG  |
| 85  | Government (General)                         | Sri Lanka        | GOVG  |
| 86  | Police                                       | Sri Lanka        | POL   |
| 87  | Private Citizens & Property                  | Sri Lanka        | PCP   |
| 88  | Transportation                               | Sri Lanka        | TRP   |
| 89  | Business                                    | Chile            | BUS   |
| 90  | Government (General)                         | Bangladesh       | GOVG  |
| 91  | Private Citizens & Property                  | Bangladesh       | PCP   |
| 92  | Private Citizens & Property                  | Cambodia         | PCP   |
| 93  | Transportation                               | Cambodia         | TRP   |
| 94  | Police                                       | Chile            | POL   |
| 95  | Utilities                                    | Yemen            | UTL   |
| 96  | Telecommunication                            | El Salvador      | TCM   |
| 97  | Business                                     | El Salvador      | BUS   |
| 98  | Business                                    | Italy            | BUS   |
| 99  | Government (General)                         | Greece           | GOVG  |
| 100 | Private Citizens & Property                  | Sierra Leone     | PCP   |
| 101 | Business                                    | Greece           | BUS   |
| 102 | Religious Figures/Institutions               | Indonesia        | RFI   |
| 103 | Transportation                               | Israel           | TRP   |
| 104 | Private Citizens & Property                  | Lebanon          | PCP   |
| 105 | Police                                       | Macedonia        | POL   |
| 106 | Private Citizens & Property                  | Myanmar          | PCP   |
| 107 | Private Citizens & Property                  | Namibia          | PCP   |
| 108 | Private Citizens & Property                  | Nepal            | PCP   |
| 109 | Transportation                               | Pakistan         | TRP   |
| 110 | Military                                     | Syria            | MIL   |
| 111 | Utilities                                    | Philippines      | UTL   |
| 112 | Educational Institution                      | United States    | EDI   |
| 113 | Utilities                                    | Bolivia          | UTL   |
| Page | Private Citizens & Property, Zambia                        | PCP_ZMB |
|------|-----------------------------------------------------------|---------|
|      | Private Citizens & Property, Central African Republic     | PCP_CAF |
|      | Transportation, India                                     | TRP_IND |
|      | Private Citizens & Property, Niger                        | PCP_NER |
|      | Religious Figures/Institutions, Yemen                     | RFI_YEM |
|      | Utilities, Iran                                           | UTL_IRN |
|      | Refugee Camp, Iraq                                        | RC_IRQ  |
|      | Refugee Camp, Sudan                                       | RC_SDN  |
|      | Airports & Aircraft, Afghanistan                          | AA_AFG  |
|      | Airports & Aircraft, Japan                                | AA_JPN  |
|      | Business, Afghanistan                                     | BUS_AFG  |
|      | Business, Bangladesh                                      | BUS_BGD  |
|      | Business, Egypt                                           | BUS_EGY |
|      | Business, Honduras                                        | BUS_HND  |
|      | Business, India                                           | BUS_IND  |
|      | Business, Kenya                                           | BUS_KEN |
|      | Business, Lebanon                                         | BUS_LBN |
|      | Business, Libya                                           | BUS_LBY |
|      | Business, Mexico                                          | BUS_MEX |
|      | Business, Nicaragua                                       | BUS_NIC |
|      | Business, Nigeria                                         | BUS_NGA |
|      | Business, Pakistan                                        | BUS_PAK |
|      | Business, Somalia                                         | BUS_SOM |
|      | Business, South Africa                                    | BUS_ZAF |
|      | Business, Syria                                          | BUS_SYR |
|      | Business, Thailand                                        | BUS_THA |
|      | Business, Yemen                                          | BUS_YEM |
|      | Educational Institution, Afghanistan                      | EDI_AFG |
|      | Educational Institution, India                            | EDI_IND |
|      | Educational Institution, Italy                            | EDI_ITA |
|      | Educational Institution, Nepal                            | EDI_NPL |
|      | Educational Institution, Spain                            | EDI_ESP |
|      | Educational Institution, Thailand                         | EDI_THA |
|      | Educational Institution, Turkey                           | EDI_TUR |
|      | Government (Diplomatic), Cuba                             | GOVD_CUB |
|      | Government (Diplomatic), France                           | GOVD_FRA |
|      | Government (Diplomatic), Peru                             | GOVD_PER |
|      | Government (Diplomatic), United States                    | GOVD_USA |
|      | Government (General), Argentina                           | GOVG_ARG |
|      | Government (General), Chile                               | GOVG_CHL |
|      | Government (General), Germany                             | GOVG_DEU |
|      | Government (General), Great Britain                       | GOVG_GBR |
|      | Government (General), Guatemala                           | GOVG_GTM |
|      | Government (General), India                               | GOVG_IND |
|      | Government (General), Iraq                                | GOVG_IRQ |
|      | Government (General), Israel                              | GOVG_ISR |
|      | Government (General), Italy                               | GOVG_ITA |
|      | Government (General), Japan                               | GOVG_JPN |
|      | Government (General), Kenya                               | GOVG_KEN |
|      | Government (General), Libya                               | GOVG_LBY |
|      | Government (General), Nicaragua                           | GOVG_NIC |
|      | Government (General), Nigeria                             | GOVG_NGA |
|   |   |   |
|---|---|---|
| 166 | Government (General) | Northern Ireland | GOVG_NIRL |
| 167 | Government (General) | Pakistan | GOVG_PAK |
| 168 | Government (General) | Russia | GOVG_RUS |
| 169 | Government (General) | Thailand | GOVG_THA |
| 170 | Government (General) | Ukraine | GOVG_UKR |
| 171 | Government (General) | United States | GOVG_USA |
| 172 | Government (General) | West Bank and Gaza Strip | GOVG_WBGGS |
| 173 | Journalists & Media | Afghanistan | JAM_AFG |
| 174 | Journalists & Media | Algeria | JAM_DZA |
| 175 | Journalists & Media | Chile | JAM_CHL |
| 176 | Journalists & Media | El Salvador | JAM_SLV |
| 177 | Journalists & Media | Iraq | JAM_IRQ |
| 178 | Journalists & Media | Italy | JAM_ITA |
| 179 | Journalists & Media | Pakistan | JAM_PAK |
| 180 | Journalists & Media | Peru | JAM_PER |
| 181 | Journalists & Media | Somalia | JAM_SOM |
| 182 | Journalists & Media | Spain | JAM_ESP |
| 183 | Journalists & Media | Yemen | JAM_YEM |
| 184 | Military | Afghanistan | MIL_AFG |
| 185 | Military | Colombia | MIL_COL |
| 186 | Military | Democratic Republic of the Congo | MIL_COD |
| 187 | Military | Great Britain | MIL_GBR |
| 188 | Military | India | MIL_IND |
| 189 | Military | Iraq | MIL_IRQ |
| 190 | Military | Libya | MIL_LBY |
| 191 | Military | Nigeria | MIL_NGA |
| 192 | Military | Northern Ireland | MIL_NIRL |
| 193 | Military | Pakistan | MIL_PAK |
| 194 | Military | Philippines | MIL_PHL |
| 195 | Military | Russia | MIL_RUS |
| 196 | Military | Spain | MIL_ESP |
| 197 | Military | Sri Lanka | MIL_LKA |
| 198 | Military | Turkey | MIL_TUR |
| 199 | Military | Yemen | MIL_YEM |
| 200 | NGO | Afghanistan | NGO_AFG |
| 201 | Police | Bangladesh | POL_BGD |
| 202 | Police | El Salvador | POL_SLV |
| 203 | Police | France | POL_FRA |
| 204 | Police | Great Britain | POL_GBR |
| 205 | Police | Indonesia | POL_IDN |
| 206 | Police | Italy | POL_ITA |
| 207 | Police | Libya | POL_LBY |
| 208 | Police | Mexico | POL_MEX |
| 209 | Police | Nepal | POL_NPL |
| 210 | Police | Nigeria | POL_NGA |
| 211 | Police | Russia | POL_RUS |
| 212 | Police | Somalia | POL_SOM |
| 213 | Police | Thailand | POL_THA |
| 214 | Police | Ukraine | POL_UKR |
| 215 | Police | West Bank and Gaza Strip | POL_WBGGS |
| 216 | Private Citizens & Property | Chad | PCP_TCD |
| Page | Private Citizens & Property | Code  |
|------|-----------------------------|-------|
| 218  | Chile                        | PCP_CHL |
| 219  | Egypt                        | PCP_EGY |
| 220  | Ethiopia                     | PCP_ETH |
| 221  | France                       | PCP_FRA |
| 222  | Germany                      | PCP_DEU |
| 223  | Great Britain                | PCP_GBR |
| 224  | Greece                       | PCP_GRC |
| 225  | Indonesia                    | PCP_IDN |
| 226  | Iran                         | PCP_IRN |
| 227  | Ireland                      | PCP_IRL |
| 228  | Italy                        | PCP_ITA |
| 229  | Kenya                        | PCP_KEN |
| 230  | Mexico                       | PCP_MEX |
| 231  | Nicaragua                    | PCP_NIC |
| 232  | Russia                       | PCP_RUS |
| 233  | South Africa                 | PCP_ZAF |
| 234  | Spain                        | PCP_ESP |
| 235  | Thailand                     | PCP_THA |
| 236  | Afghanistan                  | RFI_AFG |
| 237  | Colombia                     | RFI_COL |
| 238  | India                        | RFI_IND |
| 239  | Iraq                         | RFIIRQ |
| 240  | Nigeria                      | RFI_NGA |
| 241  | Pakistan                     | RFI_PAK |
| 242  | Philippines                  | RFI_PHL |
| 243  | Somalia                      | RFI_SOM |
| 244  | United States                | RFI_USA |
| 245  | Colombia                     | TCM_COL |
| 246  | India                        | TCM_IND |
| 247  | Peru                         | TCM_PER |
| 248  | Philippines                  | TCM_PHL |
| 249  | Spain                        | TCM_ESP |
| 250  | India                        | TNSM_IND |
| 251  | Iraq                         | TNSMIRQ |
| 252  | Libya                        | TNSMLBY |
| 253  | Northern Ireland              | TNSMNIRL |
| 254  | Pakistan                     | TNSMPAK |
| 255  | Spain                        | Tourists_ESP |
| 256  | Afghanistan                  | TRP_AFG |
| 257  | Chile                        | TRP_CHL |
| 258  | El Salvador                  | TRP_SLV |
| 259  | Great Britain                | TRP_GBR |
| 260  | Iraq                         | TRP_IRQ |
| 261  | Kenya                        | TRP_KEN |
| 262  | Nepal                        | TRP_NPL |
| 263  | Nicaragua                    | TRP_NIC |
| 264  | Nigeria                      | TRP_NGA |
| 265  | Northern Ireland              | TRP_NIRL |
| 266  | Peru                         | TRP_PER |
| 267  | Philippines                  | TRP_PHL |
| 268  | Russia                       | TRP_RUS |
| 269  | South Africa                 | TRP_ZAF |
Table 4. Names and abbreviations of Targets that appear in the backbone structure (1970-2016).

The list of top-50 actor pairs (source-target abbreviations) along with their weights (frequencies of interactions) that appear in the backbone of the global terrorist network with 470 nodes are given in Table S5 and 427 unique edges.

| Sr. No. | Source       | Target       | Weight |
|---------|--------------|--------------|--------|
| 1       | Taliban_AFG  | POL_AFG      | 1854   |
| 2       | ISIL_IRQ    | PCP_IRQ      | 1303   |
| 3       | Taliban_AFG  | PCP_AFG      | 1086   |
| 4       | Taliban_AFG  | GOVG_AFG     | 810    |
| 5       | BH_NGA      | PCP_NGA      | 740    |
| 6       | SPSL_PER    | PCP_PER      | 733    |
| 7       | FMLN_SLV    | UTL_SLV      | 713    |
| 8       | SPSL_PER    | GOVG_PER     | 693    |
| 9       | SPSL_PER    | BUS_PER      | 670    |
| 10      | SPSL_PER    | POL_PER      | 552    |
| 11      | ETA_ESP     | POL_ESP      | 530    |
| 12      | SPSL_PER    | UTL_PER      | 506    |
| 13      | ETA_ESP     | BUS_ESP      | 495    |
| 14      | ISIL_IRQ    | POL_IRQ      | 451    |
| 15      | CPI-Maoist_IND | PCP_IND       | 448    |
| 16      | IRA_GBR     | POL_NIRL     | 433    |
| 17      | FARC_COL    | PCP_COL      | 391    |
| 18      | ASB_SOM     | PCP_SOM      | 387    |
| 19      | KWP(PKK)_TUR | POL_TUR     | 366    |
| 20      | PE_NGA      | PCP_NGA      | 361    |
| 21      | CPI-Maoist_IND | POL_IND       | 341    |
| 22      | FARC_COL    | POL_COL      | 333    |
| 23      | FMLN_SLV    | PCP_SLV      | 330    |
| 24      | ASB_SOM     | GOVG_SOM     | 324    |
| 25      | Maoists_IND | POL_IND      | 315    |
| 26      | IRA_GBR     | PCP_NIRL     | 296    |
| 27      | NPA_PHL     | POL_PHL      | 293    |
| 28      | Houthi_YEM  | PCP_YEM      | 292    |
| 29      | NPA_PHL     | BUS_PHL      | 291    |
| 30      | CPI-Maoist_IND | GOVG_IND     | 278    |
| 31      | LTTE_LKA    | PCP_LKA      | 275    |
| 32      | IRA_GBR     | BUS_NIRL     | 270    |
| 33      | TTP_PAK     | PCP_PAK      | 267    |
| 34      | FARC_COL    | BUS_COL      | 251    |
| 35      | KWP(PKK)_TUR | PCP_TUR     | 245    |
|   | FMLN_SLV | BUS_SLV |   |
|---|----------|---------|---|
| 37| ELN_COL  | UTL_COL | 230|
| 38| IRA_GBR  | BUS_GBR | 222|
| 39| AQI_IRQ  | PCP_IRQ | 221|
| 40| Maoists_IND | PCP_IND | 219|
| 41| NPA_PHL  | GOV_GPHL| 218|
| 42| BH_NGA   | POL_NGA | 218|
| 43| FARC_COL | UTL_COL | 215|
| 44| FARC_COL | GOV_GCOL| 211|
| 45| LTTE_LKA | POL_LKA | 207|
| 46| FLNC_FRA | BUS_FRA | 204|
| 47| NPA_PHL  | PCP_PHL | 200|
| 48| PE_GBR   | PCP_NIRL| 196|
| 49| TTP_PAK  | POL_PAK | 192|
| 50| ETA_ESP  | GOV_ESP | 190|

**Table 5.** Top 50 actor pairs in the backbone