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Temporal Dynamics in Covert Networks: A Case Study of the Structure behind the Paris and Brussels Attacks

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ABSTRACT

This paper analyzes the network behind the Paris and Brussels attacks and related plots that were organized in the name of Islamic State. It answers the questions how the network was structured and how it developed over time. The database used contains highly reliable information from the judiciary and the intelligence community. It is therefore among the first to allow for statistical analysis of the typology of a covert network, while also being reliable and detailed enough to admit for an analysis of the covert network chronological development. The findings are that the network was centralized and thus vulnerable to targeted attacks against the most central nodes. The network developed in three phases: (1) construction of local cells, predominantly based on pre-existing ties; (2) travel to Islamic State and merger with a larger network; (3) consolidation before carrying out an attack. In addition, it is found that (1) most network analyses of covert networks understate the importance of peripheral nodes, and (2) that analyzing the final configuration of the network alone does not necessarily lead to correct conclusions, as it ignores the underlying structures of pre-existing networks.

KEYWORDS

Islamic State; terrorism; social network analysis; Paris attacks; Brussels attacks; Verviers; covert networks; temporal dynamics

Introduction

In 2015 and 2016, France and Belgium were the targets of multiple terrorist plots. Less than a year after the attacks on the offices of Charlie Hebdo, Paris was struck again on November 13th, 2015. Three suicide bombers exploded their belts around the Stade de France, another group targeted several restaurants in a fusillade and three shooters held the visitors of the Bataclan concert hall hostage, killing a large number of them. Islamic State would later claim responsibility for the attacks.

When investigating these events, officials quickly identified several connections with a network of violent, radicalized Islamic State supporters in Belgium. Many of the attackers were Belgian themselves and clear links were found between some of the attackers and a jihadist cell from the East-Belgian city Verviers. This cell had been rounded up in January 2015, and a court case had followed soon thereafter.

Throughout the months after November 13th, the three surviving Paris attackers were arrested or killed and several safe houses were discovered. As they saw the police closing

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in around them, five remaining members of the support network attacked Zaventem airport and metro station Maalbeek in Brussels on March 22nd, 2016. For this second round of attacks, thirty-one fatalities and 300 wounded victims have been reported.[1] In the case of Paris, 352 people were wounded, and 130 were killed.[2] These numbers make the events some of the deadliest ones on European soil in the twenty-first century.

Although the network responsible for these attacks was largely hidden, it is obvious that the events had a devastating impact on society. In order to prevent this in the future, it is critical to understand how the network became capable of carrying out operations of this scale. A network analysis can help, as uncovering the structure of the network can expose its strengths and vulnerabilities and can reveal the circumstances under which it was able to develop.[3]

Studies like these are relatively common despite the fact that obtaining reliable data about covert networks is challenging. As a result, a prevailing criticism of the field of terrorism studies is the inadequacy of its sources of information.[4] Moreover, while multiple scholars have applied methods of network analysis to terrorist groups, they tend to focus on the final configuration of these networks and not on how they came into existence.[5] This ignores the dynamic character of real-world networks.

This article makes a significant contribution in this regard. Based on extensive data from both the judiciary and intelligence agencies, it provides new perspectives into this covert network, its links to Islamic State, and how it developed in such a way that it could execute the attacks on November 13th and March 22nd. In addition, it compares the findings to existing studies to identify where the impact of missing data is most apparent. The research is guided by two closely related empirical questions, namely how the network was structured and how it developed over time. It addresses not only the static, final configuration of the network but also its temporal component and underlying structures.

To the best of my knowledge, the database used for this study is the first to allow for statistical analysis of the typology of a covert network, while also being reliable and detailed enough to admit for an analysis of a network's chronological development. Consequently, this study does not merely have implications for this specific case, but also for the research of covert networks more generally. Its main findings are two-fold. First, most network analyses of covert networks understate the importance of peripheral nodes, causing the networks to appear more centralized than they are. Second, many analysts draw conclusions from the final configuration of the network alone, while that topology is not necessarily representative of the early stages of the network. In other words, the underlying structures are ignored if one only focuses on the final result.

To clarify, the framework presented in this article will not extend to the more complex analyses that are common in the study of social networks. Instead, its focus lies on applying the methodology to a real-world network and contrasting it with the existing literature. In doing so, it reveals where other studies might come short and what can be done to address these limitations in the future.

The paper is structured as follows. It starts out with a review of the literature, including previously conducted studies of terrorist networks, their structures and development, and the role of ideology. In the subsequent section, the research design and methodology are discussed as well as the related limitations. The analysis answers the research questions about the structure of the network and its development over time. Then, the discussion further investigates the gap that emerged in the analysis, i.e. how the network was able to consolidate. The section on implications addresses how this article fits into the existing body of literature on terrorist networks and covert networks more generally. It also discusses the effect of missing data on such studies. The final section concludes.

Literature review

Several case studies on the structure of terrorist networks have been conducted so far, particularly in the aftermath of 9/11. A variety of network structures is observable across different case studies, ranging from centralized to decentralized.

The idea of terrorist groups as structured organizations with hierarchies and assigned roles has been promulgated by authors like Crenshaw,[6] Richardson[7] and Nesser.[8] The Jemaah Islamiyah cell, responsible for the bombings in Bali in 2002, matches this topology.[9] Two commanders in this cell had exceptionally high centrality scores, which made their operations highly efficient while increasing the risk of detection. Harris-Hogan came to a similar conclusion in an examination of neo-jihadist networks in Australia.[10]

According to Gutfraind and Genkin, the network behind the Paris and Brussels attacks (the same one studied in the present paper) had a centralized structure as well.[11] Having collected data from open sources, the authors identified 146 connections between a total of seventy-one nodes in the network. The most central individuals were Abdelhamid Abaaoud and Salah Abdeslam and the distribution of the nodal degrees and betweenness were well-described by a power-law. In the implications section of this paper, I compare their findings to my own in more detail.

Conversely, various scholars have found more decentralized and sparse topologies in terrorist networks. For example, Krebs found the Hamburg cell behind the 9/11 attacks to be quite loosely connected, although there was an underlying basis of strong, trusted prior contacts.[12] Similarly, Rodriguez found that loose connections were a key feature of the network behind the Madrid train bombings of March 11th, 2004.[13] It made the network resilient in the face of arrests and mission failures, as well as flexible in its operations.

With regard to the development of jihadist networks, many of them appear to emerge in an isolated fashion. Indeed, Vidino studied known jihadist conspiracies in the EU from 2006 to 2010 and found that network formation occurs through a bottom-up process, instead of being instigated by an external organization.[14] 70 percent of the plots appeared to be organized independently of each other, even though the most extensive plots tended to have operational connections to groups operating outside of Europe (i.e. Al Qaeda or associated movements). The radicalization process would usually be initiated in small groups of friends who were sometimes egged on by a recruiter. Subsequently, these separate groups would reach out to organizations operating outside of Europe.

When it comes to radicalization and recruitment, the dynamics of jihadi networks are not significantly different from other clandestine networks. Importantly, pre-existing networks and group pressures play a significant role in expanding a group or movement of any kind.[15] Kalyvas, for example, cites several studies that show that processes of joining a group are usually rooted in network dynamics. Friendship and kin ties were the best predictors of joining a movement, while ideology played a less central role.[16] In a similar vein, Erickson and Krebs both argued that clandestine organizations (including terrorist groups) rely on trusted prior contacts for recruitment, acquiring resources, and their effective functioning more generally.[17] These claims are supported by empirical evidence from e.g. the International Center for Counter Terrorism (ICCT), Baker and Faulkner, Sageman and Richardson.[18] Scholars of social movements have come to similar conclusions as well, emphasizing the importance of one's social environment and socio-economic conditions more generally.[19]

These studies appear to suggest that ideology does not play a significant role at all. Instead, it would merely function as a facilitator, justification, or common repertoire.[20] Tilly confirms this hypothesis as his research showed that mobilization does not necessarily occur along ideological lines, but that it can also be based on neighborhood and friendship networks and community solidarities.[21] Likewise, Kalyvas has argued that in order to understand violence, one has to take into account local pre-existing cleavages, and Fagan, Wilkinson and Davies emphasize the importance of the social contagion of violence.[22] Ideology would thus be used as a tool, to be adapted to the local context, and to be changed in order to match and justify the objectives of a given group.[23]

The implications of the above research are in line with the work of the intelligence community. The authors largely agree that coordinated attacks against social hubs are most effective to degrade decentralized networks. In centralized structures, a targeted operation against the leadership is most productive. Furthermore, small-scale operations are difficult (if not impossible) to eradicate completely, but without the support and inspiration of the larger network, enthusiasm will fade out. Finally, pre-existing networks, solidarities and cleavages are among the strongest predictors of involvement and should therefore be top of mind for any investigator.

The main limitation of studies of clandestine networks is that the data is usually not detailed or accurate enough. For example, Vidino writes that having to rely mostly on open sources inevitably provides only partial knowledge of each case.[24] Similarly, Xu and Chen caution their readers to take care when interpreting their findings because hidden information might have skewed their results.[25] And while studying the same network as Krebs, Sageman found some inaccuracies and neglected yet important links.[26] In the section on implications, I consider the added value of a dataset that is highly reliable and more detailed and accurate than open source information.

Research design

The aim of this paper is to learn how the network behind the Paris and Brussels attacks was structured and how it developed over time. The underlying goal is to learn how events like these can be prevented. As such, the research design is strongly informed by previous studies of network disruption.

In establishing the boundaries of the network, I took a pragmatic approach: everyone who was included in the data would be included in the dataset. The boundaries of the dataset thus correspond with those of the available information. In a similar vein, the temporal scope of this study is January 1, 2012 to April 30, 2016, i.e. about one week after the Brussels attacks took place.

The data is collected from court documents, reports from intelligence agencies, and police investigations, supplemented by several open source documents. The source material consists of a 203 page document related to the prosecution of the members of the cell in Verviers, a total of 1119 pages of reports and investigations conducted by the French authorities in the aftermath of the Paris attacks, and 181 pages of reports from the Belgian authorities, predominantly related to the aftermath of the Brussels attacks. These documents contain reliable information on the actors involved in particular actions.

All communications and pre-existing relationships between individuals have been collected by means of a proxy for the connections between individuals. If available, the date and time of communications were included in the database. In total, the network consisted of 161 individuals, 131 of which were extremists. An "extremist" was defined as someone who is known to have traveled to Islamic State territory, who has made an attempt to do so, has supported and/or pledged allegiance to Islamic State, and/or who has been convicted or suspected of "participation in a terrorist organization". The remaining thirty members of the network were individuals who knowingly or unknowingly supported the network (e.g. by providing safe houses or other services) but who were not radicalized themselves.

The analysis of the network is based on (1) a static network graph of the aggregated network, (2) a stop-motion video of how the network developed throughout the years, and (3) three tables and their derivatives containing data on various centrality measures.

As for the network graphs, the ties in the network are weighted. As Granovetter wrote in his seminal piece, the weight of a tie is generally a function of duration, emotional intensity, intimacy, and exchange of services.[27] In the present network, the increasing weight of the ties over time reflects the repeated interactions between the nodes as a proxy for the above. For visibility purposes, the weights are reduced to a score of 1 to 3 in the graphs, while the exact scores have been retained in the centrality tables.

The video consists of fifty-two network graphs with a constant node lay-out. The graphs represent the configuration of the network in each month between January 2012 to April 2016. They are shown in sequential order for one second each, thereby demonstrating when the ties are formed. The video can be consulted at https://www.youtube.com/watch?v=NGJhFaVr_xY .

The three tables contain data on the centrality scores of each of the 161 nodes for all fifty-two months. Considering that this gives us more than 25.000 data points, this paper includes three derived tables (…) (Tables 1–3) with basic statistical measures (i.e. the range, mean, median, and mode). Furthermore, I added a table of the top 10 percent of the most central nodes according to the three centrality measures for each moment in time (Tables 4–6). The full versions of the tables are included in the Appendix.

Centrality measures help us to determine which nodes were the most important, and therefore which individuals should have been targeted at which point in time. Many centrality measures are available, but for the present study, I selected degree, strength, and betweenness. Metrics like closeness centrality and Eigenvector centrality were not included, as those are not meaningful or well suited for disconnected networks.

The degree of a node is defined as the total amount of connections of that node. A node with many connections can thus be described as having a high degree centrality. This

Table 1. Degree.

	Jan 2012	Jul 2012	Jan 2013	Jul 2013	Jan 2014	Jul 2014	Jan 2015	Jul 2015	Jan 2016	Apr 2016
Min	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0
25%	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	1.0	2.0
Median	0.0	0.0	0.0	1.0	1.0	1.0	1.0	2.0	2.0	3.0
75%	1.0	1.0	1.0	1.0	2.0	2.0	3.3	4.0	5.0	7.0
Max	7.0	7.0	7.0	7.0	11.0	15.0	26.0	30.0	42.0	54.0
Mean	0.8	0.9	0.9	1.0	1.2	2.0	2.7	2.9	4.2	5.2
Mode	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	1.0	2.0

Table 2. Strength.

	Jan 2012	Jul 2012	Jan 2013	Jul 2013	Jan 2014	Jul 2014	Jan 2015	Jul 2015	Jan 2016	Apr 2016
Min	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0
25%	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	2.0	2.0
Median	0.0	0.0	0.0	1.0	1.0	1.0	2.0	2.0	3.0	4.0
75%	1.0	1.0	1.3	2.0	2.0	3.0	4.0	5.0	7.0	8.0
Max	7.0	7.0	8.0	8.0	13.0	20.0	37.0	43.0	57.0	81.0
Mean	0.9	0.9	1.1	1.1	1.4	2.5	3.5	3.8	5.5	7.5
Mode	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.0	2.0

Table 3. Betweenness.

	Jan 2012	Jul 2012	Jan 2013	Jul 2013	Jan 2014	Jul 2014	Jan 2015	Jul 2015	Jan 2016	Apr 2016
Min	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
25%	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Median	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
75%	0.0	0.0	0.0	0.0	0.0	0.0	1.5	18.4	66.8	78.8
Max	143.0	143.0	163.0	163.0	701.5	1179.7	2415.9	3857.1	6530.6	8620.8
Mean	4.1	4.2	4.8	5.0	19.0	34.7	63.9	94.8	155.8	176.5
Mode	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Table 4. Top 10% nodes in terms of degree centrality.

Jan 2012	Jul 2012	Jan 2013	Jul 2013	Jan 2014	Jul 2014	Jan 2015	Jul 2015	Jan 2016	Apr 2016
1	1	1	1	20	1	20	20	20	20
80	80	80	80	1	20	1	1	65	65
20	20	68	68	80	67	22	22	76	76
79	79	20	20	79	22	38	38	67	67
67	67	79	79	68	31	67	67	1	1
18	18	67	67	67	80	18	18	22	22
70	70	18	18	18	18	19	19	80	81
154	68	70	70	70	19	31	31	38	80
19	154	154	5	5	79	3	3	68	38
65	19	19	154	154	68	2	2	18	18
73	65	65	19	94	5	80	80	19	71
116	73	73	65	22	115	79	79	31	79
138	116	116	73	37	89	68	68	3	82
68	138	138	116	56	90	37	37	2	68
94	94	94	138	19	111	5	5	70	56
22	22	22	94	65	112	115	115	71	51

Table 5. Top 10% nodes in terms of strength centrality.

Jan 2012	Jul 2012	Jan 2013	Jul 2013	Jan 2014	Jul 2014	Jan 2015	Jul 2015	Jan 2016	Apr 2016
1	1	68	68	20	1	20	20	20	20
67	67	1	1	80	20	1	1	65	65
80	80	67	67	79	31	18	18	76	76
20	20	80	80	68	67	3	3	1	80
79	79	20	20	1	18	2	2	80	1
70	70	79	79	67	22	22	22	67	82
18	68	70	70	154	19	19	19	18	81
116	18	116	116	56	80	31	31	3	67
65	116	18	18	70	79	67	67	2	79
2	65	93	93	116	68	38	38	68	18
19	2	23	23	93	5	80	68	22	2
37	19	65	5	37	154	79	80	19	3
138	37	2	65	18	56	68	79	82	22
73	138	19	2	23	93	4	4	31	60
154	73	37	19	5	33	5	5	60	68
47	154	138	37	65	115	37	37	38	51

Table 6. Top 10% of nodes in terms of betweenness centrality.

Jan 2012	Jul 2012	Jan 2013	Jul 2013	Jan 2014	Jul 2014	Jan 2015	Jul 2015	Jan 2016	Apr 2016
20	20	20	20	20	20	20	20	20	20
18	18	18	18	94	1	94	94	65	67
70	70	70	70	1	94	38	56	67	65
1	1	1	1	70	22	56	38	38	51
73	73	73	73	19	70	22	1	80	38
19	19	19	19	56	56	1	22	1	22
80	80	68	80	22	5	70	70	22	1
65	67	67	68	18	31	8	7	68	40
22	65	80	67	80	18	79	76	7	68
78	22	65	145	73	19	5	79	51	76
145	78	22	65	37	80	80	51	76	79
67	68	78	22	79	73	19	80	5	72
94	145	71	78	145	37	4	5	19	3
138	94	145	71	65	21	18	19	72	80
79	138	94	94	78	79	2	18	18	81
68	79	138	138	71	145	73	4	79	4

measure is easy to compute and is used in many network analyses. However, it is solely defined for binary situations in which there is either a connection, or there is none. In other words, the degree of a node does not take into account the quality (or "weight") of the connections, despite the fact that there can be high variability in their intensity. Instead, such information is lost and consequently, the complexity of the network topology cannot be described to the same extent or as richly.[28]

The second centrality measure, strength, addresses this problem by calculating the sum of the weight of all connections of a node. For example, a node has a strength of 10 if it has 5 connections with a weight of 2. One possible limitation of this measure is the implicit assumption that the quantity and quality of the ties are equally important. A node with many weak ties could thus have the same strength as a node with a handful of strong ties.[29]

A further downside of both degree and strength centrality is that they are local metrics, i.e. they do not provide any information about the global structure of the network. As such, if one aims to disrupt the network, it would still be uncertain which nodes should be attacked. In this respect, the final measure, betweenness centrality, adds much value. It can be described as a macro-scale network metric that measures the number of times that a node appears on the shortest path between two other nodes, and therefore, to what extent it can serve as a bridge.[30] Nodes with a high betweenness centrality can act as brokers and are in a good position to control the flow of resources and information. However, one limitation is that a great proportion of nodes generally does not lie on a shortest path between any two other nodes. Therefore, many will receive the same score of 0. The present network is no exception to this.

According to Holme et al.,[31] the best approach to disrupt a network and break it into smaller units is to calculate the betweenness centrality for each iteration and to perform a targeted attack against the most central nodes. Wandelt et al. reached the same conclusion, despite the fact that this method is one of the oldest and conceptually simplest approaches.[32] Betweenness centrality is simply extremely well aligned with the aim of disrupting the main communication paths of a network, and considering that a network is a dynamic structure, it is important to adapt a strategy to its most recent iteration.[33] As Holme et al. stated, "the removals by the recalculated degrees and betweenness centralities are often more harmful than the attack strategies based on the initial network."[34] This is why this study includes the data points for each node and each month: taking a single iteration only would not be comprehensive enough.

Limitations

There are several limitations that are common in network studies like these. They relate to the methodology of the study and the quality and quantity of the data being used.

The methodology has two major limitations. First, the information is usually collected through a form of snowball sampling, emphasizing and creating bias toward the seeds and potentially missing nodes on the periphery of the network. Second, the data is often collected after the network has already carried out its mission, which may overstate the importance of those who were arrested and interrogated, while understating the role of those who did not survive or who were not captured yet.

In addition, the quality and quantity of the data come with limitations as well. Due to the secretive nature of the network, data can be ambiguous. For example, covert networks commonly use aliases and burner phones which makes it difficult to track the involvement of actors in certain events. Moreover, data can be missing completely, either because the authorities do not have the information themselves or because they do not disclose it as it could compromise an ongoing investigation or an individual. Missing or ambiguous data can leave gaps in the network, which in turn may affect the conclusions of a study.

Naturally, the present research is no exception to these limitations. The risks are that certain nodes or ties could be missing or over- or underemphasized, therefore impacting the overall structure of the network. This risk can apply to the temporal dimension as well, considering that much more data is available for 2015 and 2016 compared to 2012.

I mitigated these risks in two ways. First, I did not include any ambiguous data in the dataset and made no assumptions about any connections in the network. Instead, this information was collected in another document for separate consideration. Second, any sudden or unexplained developments in the network were recorded separately, as those usually hint at missing information. Any close relationships that had no known history, actions that were unaccounted for, or resources that appeared out of nowhere were flagged. These limitations will be addressed in more detail in the implications section of this paper, in which I compare the present study to articles that relied on less accurate sources.

Analysis

As was noted before, this analysis is based on (1) a static network graph of the aggregated network, (2) a stop-motion video of how the network developed throughout the years, and (3) three tables and their derivatives containing data on various centrality measures. Specifically, I included the following:

- Figure 1: the aggregated configuration of the network in April 2016. The nodes are colored in accordance with their degree centrality, with blue representing a high degree (many connections) and red representing a low degree. The nodes in between the two extremes are varying shades of purple.
- Figure 2: the same aggregated network with the nodes colored in accordance with their affiliated plots. These distinctions are arbitrary as the networks behind the

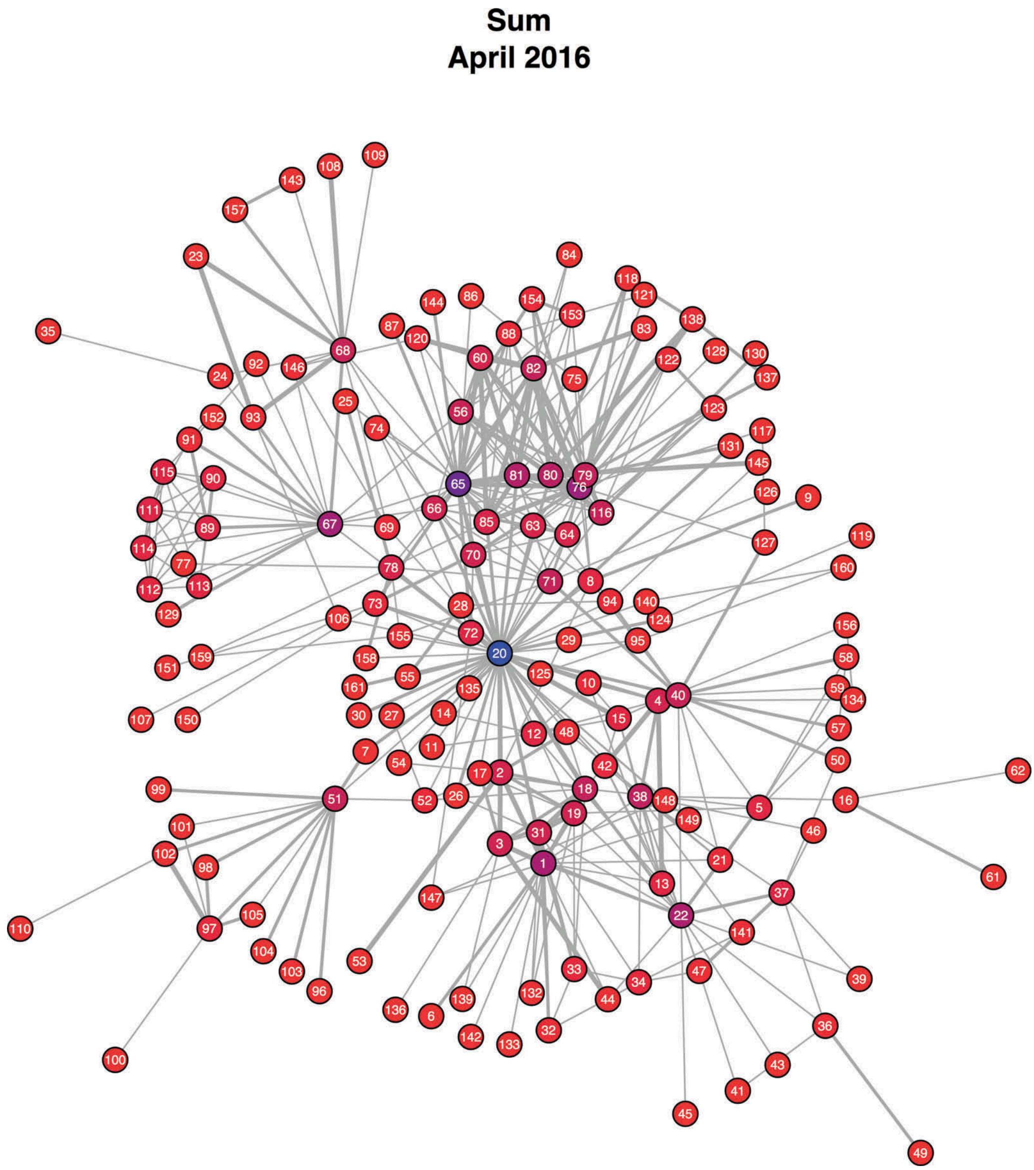

Figure 1. Configuration of the network in April 2016.

different attacks overlap to a large extent. The purpose of this visualization is to help in understanding the rest of the analysis.

- Video: a time series of the network configuration throughout time, from January 2012 until April 2016. This video can be found at https://www.youtube.com/watch?v = NGJhFaVr_xY
- Tables 1–3: three tables containing basic statistical measures for the data on the nodes' degree, strength and betweenness centrality respectively. The tables include the measures for every half year between January 2012 and April 2016.

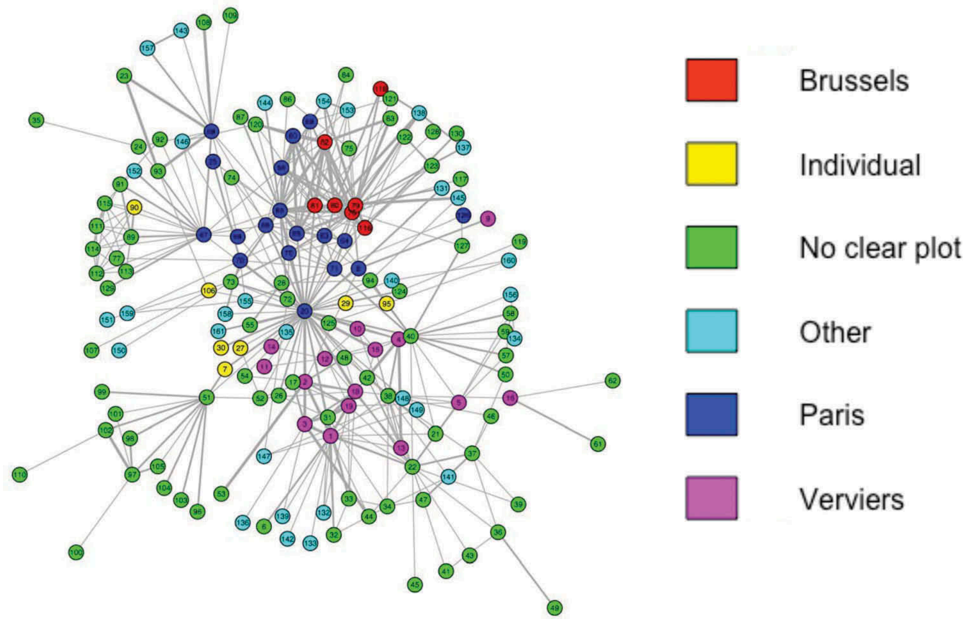

Figure 2. Configuration of the network in April 2016 with the colors indicating the affiliation of the nodes.

- Tables 4–6: three tables that include the top 10 percent of nodes in the network according to their degree, strength and betweenness centrality for every half year.
- The full tables containing the centrality measures for every node in every month. Due to the size of these tables, it was not possible to include them in the present paper.

How was the network structured?

In general terms, the network consisted of 161 individuals and 946 communications. These communications were distributed over 412 different dyads, i.e. unique combinations of two individuals. Of the 946 communications, 661 were dated, sixty-seven existed before 2012, and 218 were undated. The undated ties nearly always strengthened the dated or pre-existing ties and did not significantly alter the structure of the network.

Figures 1 and 2 and the right columns in Tables 1–3 and 4–6 represent the final, aggregated configuration of the network. I will analyze this topology before considering how the network developed over time.

According to all centrality measures, person #20 (Abdelhamid Abaaoud) was the most central figure in the network in April 2016. Abaaoud was already active in the construction of the cell in Verviers in late 2014 and evaded capture when this cell was rounded up in January 2015. Being a coordinator of Islamic State's external action command, Amn al Kharji, he would later become one of the main organizers and perpetrators of the attacks in Paris. He died in a police raid two days after those attacks, and thus did not participate directly in the events in Brussels.

The other central figures in the network were predominantly related to the Paris and Brussels attacks as well. This group formed a strong cluster while the cell in Verviers remained largely separate from them. In addition, various smaller plots have been included in this network, such as an attack on a church in Villejuif, France (Apr 2015), an attack on the Jewish museum in Brussels (Feb 2014), an attempted shooting and stabbing on a train from Amsterdam to Paris (Aug 2015), and a thwarted attack in France (Aug 2015) (see the yellow nodes in Figure 2).

When attacks like these are covered in the media, they are usually portrayed as isolated incidents. However, each of these cases was connected to the larger network, most notably through Abaaoud.[35] For example, two separate attackers had traveled to Turkey or Syria and had met Abaaoud or other coordinators of Islamic State's external action command.[36] Islamic State did not order any of these attacks in detail, instead leaving it to the attackers to select a date and a target themselves.

Like many real-world networks, this network approximates the characteristics of a scale-free network.[37] In such a network, new nodes are more likely to form connections with the most central nodes, a process known as preferential attachment. The most central nodes at $t = 0$ thus increase their connectivity at a higher rate than others, increasing the range of centrality scores as the network grows.

Such a process is visible in this network as well, as many central nodes remain central throughout time. Meanwhile, the differences in degree increased significantly. As Table 1 shows, in April 2016 half of the nodes had only three connections or less, while the node with the highest degree (i.e. Abaaoud) had fifty-four. Furthermore, Table 3 shows that the betweenness centrality of the nodes was strongly skewed to the left with a very long tail. This is not surprising, since many nodes did not lie on the shortest path between two other nodes and therefore received a score of 0. This illustrates that the network had a strong center with a periphery that branched out in many directions.

The implications of this are that the network would have been robust against random node failure, in which someone becomes inactive, is arrested, or dies. Meanwhile, the network was vulnerable to attacks targeted on nodes with a high degree or betweenness centrality.[38] In particular, shocks that occur at the initial stages of a network can sometimes lead to cascading failures.[39]

How did the network develop over time?

From the aggregated graph, one could draw the conclusion that Abaaoud could have acted as a broker between the Verviers and the Paris/Brussels cells. However, this would be incorrect as these parts of the network developed at different points in time. This section will analyze that chronological element. The development of the network is best visualized in the video, while detailed measures can be found in the tables.

Generally speaking, several local groups emerged in the network graph at different stages in time. While these cells were unconnected at first, they eventually became part of the larger network. Any preparations for specific operations appeared to accelerate this process and increased the number of connections within the cells significantly.

2012 – beginning of 2014

The starting configuration of the network (January 2012) only presents a total of sixty-six ties. Of these, thirty-eight were family ties (mostly siblings, but also cousins, and in one case, parent-child), twenty were friendship ties, and eight were romantic ties (mostly marriages). Some of these connections can be described as “dormant”: they existed but were not always reinforced by active communications.

The connected nodes formed several small clusters that did not yet form a larger network. For example, the future members of the Paris/Brussels cell formed three groups that were not connected to each other: (20, 65, 70, 73), (79, 80, 116, 138, 154), and (23, 67, 68, 93). Members of the latter two sub-groups had already been involved in extremist activities before 2012, some of them since the late 2000s. For the first group, the radicalization process started around 2012 and 2013. Over half of these individuals would be directly involved in the attacks, while the rest remained on the sidelines and in some cases provided support.

Nodes 1, 2, 18, and 19 would later become part of the Verviers cell. This cell remained largely separate from the rest of the network and developed sooner than the Paris/Brussels cell. The connections were mostly formed with coordinator Abaaoud (#20) but never with other members. It appears as though Abaaoud was consciously trying to build a network around him while others joined an operation that was already planned for them. In doing so, he strongly relied on his pre-existing network of friends and family, particularly in this period. This hints at a combination of a centralized, top-down process and bottom-up radicalization.

Importantly, the majority of the most central nodes (Tables 4–6) in the early networks had been involved in criminal activities or were closely connected to someone who did. A significant number had been sentenced for crimes like robbery and theft. This is not a surprising trend, as many foreign fighters have had previous exposure to violence and crime.

2014 – 2016

From 2014 to the beginning of 2015, the network developed especially rapidly around the plot in Verviers while other cells continued to develop in the same way as before. For example, the cluster around 67 and 68 started organizing their own training sessions in France, but their group still remained largely unconnected to the rest of the network.

Interestingly, the various clusters only merged into the larger network in the last twelve months. By then, most new connections no longer came from pre-existing networks but rather from the extremist community, as people joined jihadist groups in Europe and Islamic State territory. In a similar vein, the activity of the network increased significantly in the months before the respective attacks. Particularly the top half of the network graph became more densely connected than ever before. This is reflected in the increasing centrality scores of the individuals who were heavily involved, such as nodes 60, 65, 76, and 82. For instance, node 65 (Salah Abdeslam) organized safe-houses and provided transportation when the future attackers returned to Belgium from Islamic State territory.

An important observation is that several significant nodes became connected to the larger network at a very late stage. For example, the bombers of the Stade de France gates only traveled to Europe in October, a month before the attacks would take place. Likewise, nodes 67 and 68, who would become shooters in the Bataclan attack, would only connect to the rest of the group in September. Yet the latter two played an important role in the preparations, which caused their centrality scores to increase significantly between July

2015 and January 2016 (see Table 6). This raises the question of whether there is a gap in the data: were there any communications that occurred before September and October that the authorities could have been unaware of? I address this question in the discussion.

The influence of undated ties on the final configuration

As was noted before, the network graph for April 2016 includes all undated ties while the ones for January 2012 to March 2016 do not. In order to understand the impact of these undated ties, I compared the data for March and April of 2016.

Most notably, several new nodes appear in the tables with the top 10 percent of most central nodes (see the April 2016 columns of Tables 4–6). Examples of this are nodes 4 and 40, both of whom scored high on betweenness centrality. The reason for this sudden inclusion is that the data about their interactions was usually too vague and lacked temporal detail. For example, there is strong evidence that node 40 was a recruiter who helped many nodes in the network to radicalize, but it is usually unknown when he communicated with them. Similarly, node 4 lived in Greece and is known to have helped others to travel to Islamic State territory, but who visited him and when is largely unknown.

The influence of missing data is most apparent in cases like this. Unfortunately, this limitation remains an issue even if one has access to sources of high quality.

Assuming that this trend is similar across the network, one can infer how the limitation of missing information could have affected its structure. Two main points stand out to me. First, it is most likely that more connections and nodes existed in the periphery of the network and at the beginning of the time series (i.e. around 2012 and 2013). Second, the most central nodes in those situations are likely overemphasized, because too little information is available about the individuals around them. For instance, node 51 was interrogated by the authorities and identified many connections between him and the rest of the network. He therefore appears to be more central than others while a similar centrality score could have applied to his neighbors.

In other words, despite the high quality of the data used in this study, there are still gaps in our knowledge. It is therefore important to gather as much contextual information as we can, so that we can identify where the data is most likely to be missing. That way, one can approximate reality as much as possible.

Discussion

To summarize the analysis, a mechanism with three phases can be observed in the development of the network. First, several separate cells develop in a local context. Second, the cells become connected to each other and the larger network. Third, the network consolidates shortly before the operations take place, and individuals become even more closely connected through their coordinating communications. These phases apply to sub-groups of the network and not necessarily to the network as a whole. For example, while the Verviers cell was already in phase 3 (consolidation before attacks), the Paris and Brussels cells were still in phase 1 at that point (local, relatively unconnected cells).

As I stated before, the late involvement of some nodes in the network raises questions about whether there is a gap in the data. More specifically, it is yet unknown how the local cells were able to merge into a larger network, given that they were previously unconnected. Indeed, the Bataclan attackers lived more than 300 km away from the other nodes

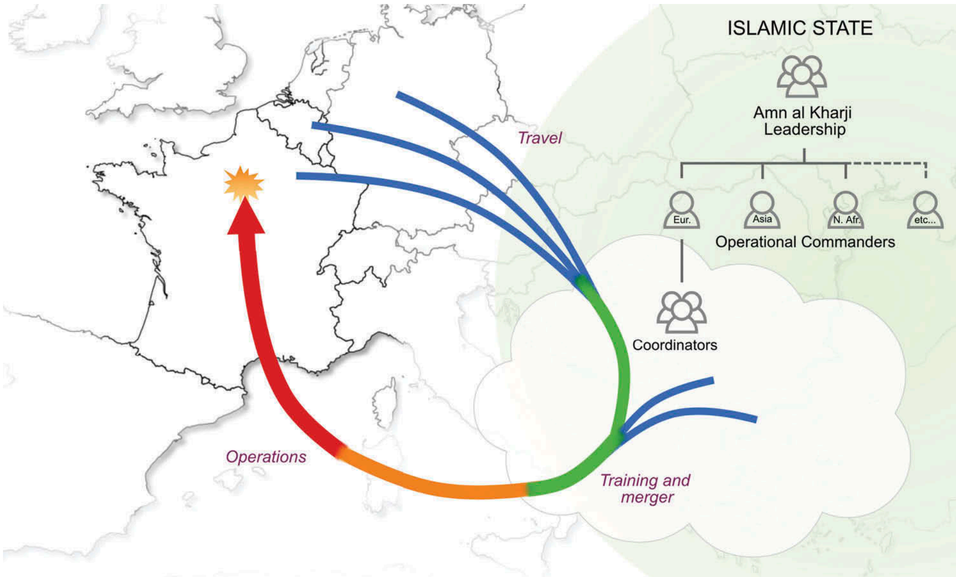

Figure 3. The mechanism of network unification.

and there is no evidence of communications before September 2015. The same applies to the Stadium bombers, who remained isolated until about a month before the attacks took place. The question is thus how these individuals became connected and capable of carrying out such large-scale, coordinated attacks.

My hypothesis is that the local cells were forged together in Islamic State territory after its members had traveled there to wage jihad. They benefited from the relatively protected setting that Islamic State provided and had plenty of opportunities to coordinate their actions. Additionally, the required assailants were recruited and trained there, which would explain the divergent origins of the resulting group and the fact that its members were not connected before. This hypothetical mechanism is visualized in Figure 3.

Given the extensive investigations of the Paris attacks, I test the hypothesis for the eighteen members of that particular cell. Of these eighteen members, nine were attackers: three at the Stade de France, three at the Bataclan theater, and three at several restaurants. The other nine helped in the organization and provided support to the attackers in the form of food, shelter, weapons, components of suicide belts, fake identity cards, transportation between safe-houses, and so forth. Each of these eighteen individuals have been profiled extensively, so it is possible to reconstruct if and when they resided in Islamic State territory.

The sub-network of the Paris cell is visualized in Figure 4. Figure 5(a–c) demonstrate its development at three different time points: March 2015, July 2015, and November 2015, when the attacks took place. Clearly, the network developed particularly rapidly in the last few months, while there were almost no connections within the group in March 2015. The connections that existed at that time were all family-ties or old friendships.

In the time between July 2015 and November 2015, the number of ties multiplied nearly eight times, from eight to sixty-two (cf. Figure 5(b, c)). Most of these ties were formed in the few weeks preceding the attacks. Previously unconnected individuals

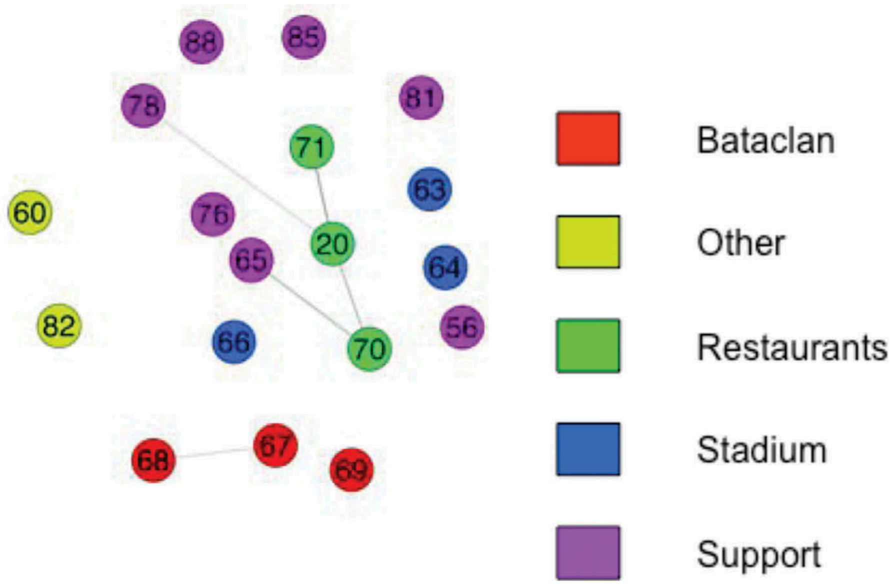

Figure 4. Individuals behind the Paris attacks and their roles, January 2012.

became a part of the larger network, and it became possible for the group to carry out coordinated operations.

Such an ad-hoc development is suitable for a single operation with a strong suicide element, in which it is not necessary for the attackers to know one another very well. Instead, it is sufficient to have a central command structure in which one or a few individuals can coordinate the actions. As the attackers themselves merely had to carry out the plan, they were relatively interchangeable. This would explain the initial isolation of nodes 63 and 64, who were mentioned previously. These two individuals were not related to one another, had never lived in France or Belgium, and there are no indications that they were ever in a position of leadership or that they took any initiative. Instead, they appear to merely have followed orders.

Since this network developed at such a late point in time, it is indeed plausible that the operatives were recruited from within Islamic State. To establish whether this could have been the case, I collected the available information about the 18 individuals and their presence in Islamic State in Table 7. The columns represent the months between January 2013 and December 2015, while each of the eighteen individuals has been assigned a row. The colors indicate when each person is believed to have been to Islamic State or to have made an attempt to go. The majority of the group spent most of their time in the de facto capital of Islamic State, Raqqa (Syria).

Overall, Table 7 shows that sixteen of the eighteen individuals had been to Islamic State or attempted to go there. Only nodes 56 and 78 never went, nor tried to. Thirteen individuals were in Syria in the months before the attacks and could thus have been involved in training sessions and coordination meetings. Moreover, of the five absentees, four had already been connected to the network before: one individual was the cousin of

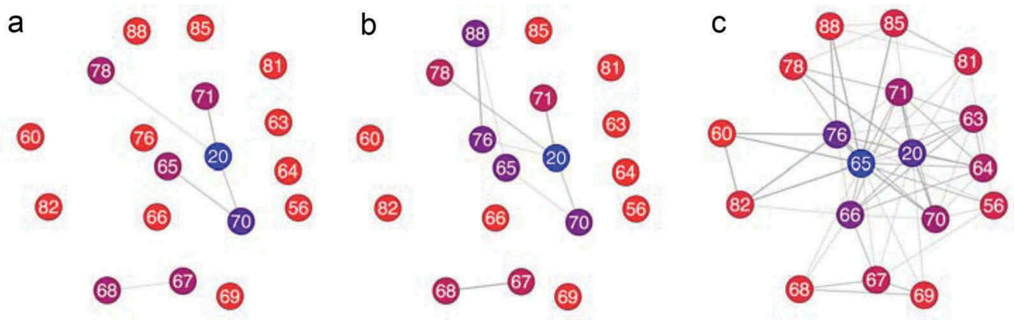

Figure 5. (a) (March 2015), (b) (July 2015), and (c) (November 2015).

node 20 (Abaaoud), another had stayed in the same prison as him, two individuals were brothers, a few others were friends, and so forth.

In conclusion, it is highly likely that the Paris attackers formed their group from inside Islamic State territory, while simultaneously drawing on pre-existing connections. The relative protection of Islamic State would have helped the coordinators to plan their actions and to find and train the assailants required for the attacks. This way, the

Table 7. Presence of individuals related to the Paris plot in Islamic state.

	2013												2014												2015											
	1	2	3	4	5	6	7	8	9	#	#	#	1	2	3	4	5	6	7	8	9	#	#	#	1	2	3	4	5	6	7	8	9	#	#	#
20	►	►	►	►	■	■	■	■	►				►	■	■	■	■	■	■	■	■	■	►	►	►	►	■	■	■	■	■	►				
56																																				
60																							►	■	■	■	■	■	■	■	■	■	►			
63																														░	░	░	░	►		
64																														░	░	░	░	►		
65																																X				
66												►	■	►	░	░	░	░								►	■	■	■	■	■	►				
67									►	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	►			
68									►	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	►			
69																													░	░	░	░	►			
70																									░	░										
71	►	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	░	░	░	░		
76																														►	■	░	░	░	░	
78																																				
81									►	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	►			
82																				►	■	■	■	■	■	■	■	■	■	■	■	■	►			
85	►	►	►	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	►	►	►			
88																										►									X	

Legend

■	Presence in Islamic State territory with near certainty
►	Travel to or from Islamic State territory
░	Presence in Islamic State territory but no certainty about arrival or departure date
X	Attempt to travel to Islamic State territory, but arrested or stopped along the way

Belgian-led group managed to connect with the French jihadis 67 and 68, as well as with suicide bombers 63 and 64.

Based on these findings, one could argue that a secure base and a sufficient amount of time are of pivotal importance to the operations of a militant group. Without either one of these ingredients, such groups would be hindered in their activities. This dynamic is not just unique to Islamic State and has previously been established in the literature. For example, Aaron stated that the loss of Afghanistan was a severe blow to Al Qaeda, and their retreat into the mountains was not much more than a refuge.[40] Consequently, he notes that "*[t]he strategic objective* of the battles in Iraq, Somalia, Chechnya, and elsewhere is to create an 'Islamic state,' *re-establishing a secure base for expanding jihad*, not only in the region, but throughout the world" (emphasis added).[41]

To a certain extent, Islamic State temporarily achieved this goal of a secure base in Iraq and Syria, providing a foundation for complex campaigns against the West and the Middle East itself. Policies that were aimed at disrupting this base thus hampered their campaigns as well. Now that Islamic State's territorial control has been diminished in that region, it will be more difficult for assailants to organize attacks of a similar scale. Instead, they are likely to resort to operations and methods that require less preparation. After all, an attack involving a vehicle as a weapon is less complicated than one for which explosives have to be produced.

Implications

In summary, the findings of this case study are that the network behind the Paris and Brussels attacks had a centralized structure with a large periphery. It initially emerged from small local groups that were based on pre-existing ties, and these groups would eventually connect to form a larger unit. The later connections were predominantly made within the extremist community, particularly when individuals started traveling to Islamic State territory.

To return to the discussion in the Literature Review, the finding that pre-existing ties are critical in the development of a network is consistent with those of Vidino, Kalyvas, Erickson, Krebs, the ICCT, Baker and Faulkner, and Richardson, as well as those of social movement scholars.[42] Most notably, Vidino stated that radicalization commonly occurred in small groups that would later connect to larger, more organized groups or networks such as Al Qaeda or affiliated movements. Writing in 2011, he stated that "this linkage is often the element that determines the level of sophistication of the plot. Although no completely successful attack has been registered in Europe since 2005, it is evident that attacks planned by individuals and networks with operational ties to groups operating outside of Europe tend to be more elaborate, professional, and potentially lethal than those hatched by individuals and networks who operate in complete independence. Training in handling explosives received overseas is, in most cases, the factor determining this difference."[43] The network investigated in the present paper fits this categorization perfectly. While the radicalization process happened in a bottom-up way, it was strengthened through the involvement of Islamic State's external action command. The attackers had received training in weapons and explosives while Abaaoud and other coordinators put the network together.

As for the role of ideology, the members of this group were not more religious than average. Instead, it was telling that the Belgian police only found one single Quran when they were rounding up the network's dozen safe houses in Brussels. Similarly, many members of the group had a criminal past and did not shy away from using violence.

Recruiters and propaganda targeted them specifically and emphasized how they could redeem themselves by converting to Islam.[44] A person's pre-existing network and socio-economic environment therefore appear to be a much better predictor for involvement than ideology. This finding is consistent with the literature.[45]

The policy implications of these findings are three-fold. First, it is imperative that bottom-up radicalization processes are hampered and, if possible, reversed. Major suspects should continue to be surveilled and particular attention has to be paid to the relationships with a long and/or strong history. Consequently, the findings from this surveillance should be analyzed in a structured manner as I have done here, in order to see if a structure can be discovered. This structure can help to inform the strategy to disrupt the network and can allow for the discovery of any irregularities that lead to new directions of research. In the present study, for example, such an irregularity led to the question of how the small groups managed to merge into a larger network.

Secondly, the authorities should prevent individuals and small groups from connecting to larger organizations, as that is what empowers them. Concrete measures can include monitoring social hubs like prisons and online fora, prohibiting travel for radicalized individuals to war zones, and preventing recruiters from radicalizing individuals any further. An additional benefit of these measures is that operations aimed at a specific country are hindered if there are no foreign fighters from that country to help with the coordination and adjustments to the local context.

Third, policy makers should focus on improving the circumstances of the communities in which radicalization is most common. As Sageman wrote, "terrorists are not passive victims, vulnerable, at risk, or brainwashed by recruiters or an ideology. They are active participants in their lives, trying to make sense of their world, constructing meanings from available cultural models and making choices accordingly."[46] Considering that a significant number of core nodes came from the same neighborhoods, addressing underlying socio-economic problems will be more effective than officially proposed solutions that focus on ideology.[47]

These policy implications are largely in line with the recommendations of other scholars and the actions that the authorities have taken. Fortunately, this has made it more difficult for extremists to replicate operations of the scale of the Paris and Brussels attacks.

In addition to policy implications, this paper has implications for academia as well. Specifically, it provides new insights into the effect of the use of more detailed and reliable data in studies of covert networks. After all, if the conclusions here are similar to those of other studies, using more extensive data might not be a necessity.

The main difference between this study and others is that this study includes more actors. For example, the 9/11 network contained sixty-two nodes,[48] the Madrid network seventy,[49] the Bali network twelve,[50] and the Paris and Brussels network by Gutfraind and Genkin counted seventy-one.[51] A network of 161 nodes can thus be considered to be large, even when we deduct the less involved nodes. To my knowledge, the only networks that were larger all had a global focus.[52]

Unsurprisingly, this difference emerges because most studies are based on open sources that focus on the most news-worthy actors such as the core attackers. This introduces a strong bias toward said core and disregards the arguable vital periphery of the network. As a result, the cells could appear smaller, more densely connected, and more heavily clustered than they would have been if the larger network had been included. Moreover, a connected plot might appear isolated, because not enough information is available about its links to a potential main network.

In the analysis, I argued that missing information could have affected the network structure in two ways. First, it was most likely that more connections and nodes existed in the periphery of the network. Second, the most central nodes in those situations were likely overemphasized, because too little information was available about the individuals around them. In order to understand the extent to which these limitations affect studies with different sources, I will now compare Gutfraind and Genkin's research to the present paper. The network that is studied is the same, but Gutfraind and Genkin relied on open source information only, while I had access to much more extensive data.

The initial results of both studies are similar. Gutfraind and Genkin found that Abdelhamid Abaaoud was the most central node in the network, and they identified a structure in which the distribution of the nodal degrees and betweenness was strongly skewed to the left. However, beyond these initial results, the findings start to deviate from each other. For example, Gutfraind and Genkin identified Salah Abdeslam (node 65 in the present paper) as "vital for connecting the network," whereas I would argue that this overstates his importance. Although Abdeslam had a pre-existing tie with Abaaoud, he only became active at a late stage. This is reflected in his betweenness centrality, which was high in April 2016 but too low to be included in the top 10 percent list from July 2014 until July 2015 (see Table 6). The temporal dimension of the network thus reveals that Abdeslam played a significantly different role from Abaaoud.[53]

Gutfraind and Genkin's research suffers from a lower accuracy as well. The cell in Verviers, for instance, contained thirty-one individuals in the present study while only four have been included in Gutfraind and Genkin's paper. Of these four, two names were incorrect, as they were seemingly drawn from an early news article that was factually inaccurate. Although Abaaoud was connected to these nodes, his role in the development of the cell was understated.

Finally, the authors were forced to make more assumptions than I did, increasing the ambiguity of the results and reducing the overall reliability of the analysis. One example is the assumption that two nodes would know each other if they had been involved in the same plot. While plausible, this is not always factual. In the case of the "attack organization," consisting of Abaaoud, Abu Muhammed al-Adnani, and several others, it was a very far stretch. Indeed, al-Adnani was a high level operative in Islamic State's external action command, and not necessarily connected to a relatively low-level coordinator like Abaaoud. Yet their group is included as a small clique, increasing the clustering in the network.

These assumptions and the lower accuracy impacted the results of the Gutfraind and Genkin paper. Their network appears more centralized because it does not include the periphery, many nodes are missing (including the seemingly isolated plots), and there is a mere 50 percent overlap between the sixteen most central actors in their network and the one presented here. But most importantly, as the temporal dimension is not included, the implication of which nodes should have been targeted is off. Salah Abdeslam only increased in importance at a very late stage, so it would not have been effective to target him. In other words, it would still be unknown how the attacks could have been prevented most efficiently.

Of course, Gutfraind and Genkin's paper was not unusual in its assumptions and limitations. However, this comparison does show that open source data is not sufficient for a thorough analysis. Missing data will always remain an issue, but as it severely impacts the conclusions it is pivotal to avoid its effects as much as possible.

In short, the main contribution of the present paper is two-fold. First, it has demonstrated that it is pivotal to take the temporal dimension into account in network analyses, as the static topology common in many network studies does not capture the full dynamics of social networks. If the goal is to disrupt a network, the most effective way is to calculate the betweenness centrality for each iteration of the network.[54] Static configurations will not be sufficient, as they cannot reveal the underlying structures and the duration of the nodes' involvement, and thus how much of a risk they pose. Networks do not appear out of nowhere, so considering how they develop is absolutely critical.

Second, this paper emphasizes the added value of reliable data and the limitations caused by missing information. Specifically, it argues that most network analyses of covert networks overestimate the role or the core actors, while understating the role of the periphery. As a result, any underlying trends could be missed, such as the connectivity of seemingly isolated events, the supporting role that non-core nodes played, or the way in which a group connected to another group.

Conclusion

This article analyzed the network behind the Paris and Brussels attacks and related plots. It found a centralized structure which emerged from small local groups. A larger network would eventually form and nodes that had been trained by Islamic State would be included. This is how the network became capable of carrying out such large-scale, lethal operations.

Fortunately, the Paris and Brussels attacks remain a unique phenomenon due to the difficulty of their organization. It will be challenging for any group to reproduce them, especially now that the authorities have taken additional measures to prevent similar events from happening in the future.

This analysis highlights the significance of the use of reliable data and warns for the limitations that emerge when data is missing. Any studies that are based on open source information alone should correct for the biases that are introduced. Specifically, it should be taken into account that the periphery of the network is most likely underestimated and that the temporal aspect should be included before any strategy recommendations can be made.

Future research should aim to further bridge the knowledge gap between social scientists, computational scientists, and the intelligence community, as these groups can enrich each other's work in significant ways. Indeed, the application of advanced methods can help political scientists and investigators to spot hidden connections and irregularities that challenge assumptions, while the thorough knowledge of specific cases can inform computational scientists of how to improve their models. Potential avenues of research include the possibilities of link prediction in covert networks, the effects of expanding the scope of the network to include more peripheral nodes and clusters, further testing of network models on real-world cases, and the inclusion of degrading social ties in those models.

On a final note, the importance of the intelligence community's efforts should be emphasized. This study has highlighted the significance of long-term, complex, and resource-intensive investigations, as well as how this work can contribute to detailed analyses. In the absence of this work, one would not have the data required to shape a strategy for the future, let alone to prevent such disruptive, lethal attacks.

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Jasmijn M. Remmers obtained a Master's degree from the Graduate Institute of International and Development Studies in Geneva, Switzerland. Her thesis focused on the network behind the Paris and Brussels attacks and she continued this research throughout her subsequent employment at the Geneva Centre for Security Policy. She currently works in the private sector in Dublin, Ireland.

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17. Bonnie H. Erickson, "Secret Societies and Social Structure," *Social Forces* 60, no.1 (1981): 188–210. https://doi.org/10.2307/2577940; Krebs, "Mapping Networks of Terrorist Cells"; See also Michael P. Noonan, *The Foreign Fighters Problem – Recent Trends and Case Studies*. Program on National Security. (Philadelphia: Foreign Policy Research Institute (FPRI), 2011); David Martin Jones, Ann Lane, and Paul Schulte, eds., *Terrorism, Security and the Power of Informal Networks* (Cheltenham ; Northampton, MA: Edward Elgar Pub, 2010); Scott Decker and David Pyrooz, "Gangs, Terrorism, and Radicalization," *Journal of Strategic Security* 4, no. 4 (2011). http://dx.doi.org/10.5038/1944-0472.4.4.7.
18. ICCT, "The Foreign Fighters Phenomenon in the European Union – Profiles, Threats & Policies," *The Hague*, April, 2016. http://icct.nl/wp-content/uploads/2016/03/ICCT-Report_Foreign-Fighters-Phenomenon-in-the-EU_1-April-2016_including-AnnexesLinks.pdf; Wayne E. Baker, and Robert R. Faulkner, "The Social Organization of Conspiracy: Illegal Networks in the Heavy Electrical Equipment Industry," *American Sociological Review* 58, no. 6 (1993): 837–60; Marc Sageman, *Understanding Terror Networks* (University of Pennsylvania Press, 2004). http://www.jstor.org/stable/j.ctt3fhfxz; Richardson, *What Terrorists Want: Understanding the Enemy, Containing the Threat*. In interviews with former members of terrorist groups, Richardson found that many spoke of a strong emotional draw to join their brothers and friends; ideology was often only of secondary importance.
19. McAdam et al., *Dynamics of Contention*; della Porta, *Clandestine Political Violence*; H. Kriesi, "Political Context and Opportunity," in *The Blackwell Companion to Social Movements,* edited by David A. Snow, Sarah A. Soule and Hanspeter Kriesi (Oxford, UK: Blackwell Publishing, 2004), 67–86.
20. Della Porta, *Clandestine Political Violence*.
21. Charles Tilly, *The Vendée* (Cambridge, MA: Harvard University Press, 1964). To be specific, Tilly investigated the origins of the Vendée counterrevolution in Western France in the 1790s. He found that there was no consistent pattern of group formation along class-lines. Instead, the local clergy was split by the demand to take a loyalty oath to the new, post-1789 government. Those who refused eventually became the new opposition, and the local communities followed their lead out of solidarity. For a similar study about mobilization in the Paris commune of 1891, see Roger V. Gould, "Multiple Networks and Mobilization in the Paris Commune, 1871," *American Sociological Review* 56 (1991): 716–29.
22. Kalyvas, "'New' and 'Old' Civil Wars: A Valid Distinction?"; Jeffrey Fagan, Deanna Wilkinson, and Garth Davies, "Social Contagion of Violence," in *The Cambridge Handbook of Violent Behavior and Aggression*, edited by Daniel J. Flannery, Alexander T. Vazsonyi, and Irwin D. Waldman (Cambridge, UK: Cambridge University Press, 2007), 688–727.
23. Francisco Sanin and Elisabeth Wood, "Ideology in Civil War: Instrumental Adoption and Beyond." *Journal of Peace Research* 51, no. 2 (2014): 213–26.
24. Lorenzo Vidino, "Radicalization, Linkage, and Diversity."
25. Xu and Chen, "The Topology of Dark Networks," 58–65.
26. Sageman, *Understanding Terror Networks*.
27. Mark Granovetter, "The Strength of Weak Ties," *American Journal of Sociology* 78, no. 6 (1973): 1360–1380.

28. A. Barrat, M. Barthélemy, R. Pastor-Satorras, and A. Vespignani, "The Architecture of Complex Weighted Networks," *PNAS* 101, no. 11 (March 2004): 3747–52; Tore Opsahl, Filip Agneessens, and John Skvoretz, "Node Centrality in Weighted Networks: Generalizing Degree and Shortest Paths," *Social Networks* 32, no. 3 (July 2010): 245–51. https://doi.org/10.1016/j.socnet.2010.03.006.
29. Further research has been done on the proportion to which degree and weight are important. For example, the following study introduced a tuning parameter in an attempt to combine both degree and strength: Opsahl et al., "Node Centrality in Weighted Networks," 245–51.
30. Sebastian Wandelt, Xiaoqian Sun, Daozhong Feng, Massimiliano Zanin, and Shlomo Havlin, "A Comparative Analysis of Approaches to Network-Dismantling," *Scientific Reports* 8, no. 1 (2018):1–15.
31. Petter Holme, Beom Jun Kim, Chang No Yoon, and Seung Kee Han, "Attack Vulnerability of Complex Networks," *Physical Review E* 65 (2002). https://doi.org/10.1103/PhysRevE.65.056109.
32. See Wandelt, et al., "A Comparative Analysis of Approaches to Network-Dismantling." The only downside of this method is that it is computationally intensive, which could pose a problem when analyzing larger networks. Fortunately, this problem does not translate to the present network as it is relatively small.
33. Dan Braha and Yaneer Bar-Yam, "From Centrality to Temporary Fame: Dynamic Centrality in Complex Networks," *Complexity* 12 no. 2 (2006): 59–63.
34. Holme et al., "Attack Vulnerability of Complex Networks", 056109-1.
35. Mariano Castillo and Paul Cruickshank, "Abdelhamid Abaaoud: Who Is Paris Attacks 'Ringleader'?" *CNN*, November 19, 2015. http://www.cnn.com/2015/11/16/europe/paris-terror-attack-mastermind-abdelhamid-abaaoud/index.html.
36. This coordinator was Fabien Clain, who occupied a similar position in Amn al Kharji as Abdelhamid Abaaoud.
37. For more information on scale-free networks, see Albert-Laszlo Barabasi and Reka Albert, "Emergence of Scaling in Random Networks," *Science* 286 (1999): 509–12. Barabasi and Albert's model has three main ingredients: 1) an initial condition of m° vertices and no edges; 2) growth, i.e. a new vertex is added every step; 3) preferential attachment of edges, i.e. there is a higher probability that new nodes become attached to nodes with a higher degree (see also Holme et al., "Attack Vulnerability of Complex Networks," 056109-1).
38. Holme et al., "Attack Vulnerability of Complex Networks," 056109-1; Hyoungshick Kim, and Ross Anderson, "Temporal Node Centrality in Complex Networks," *Physical Review E* 85, no. 2 (2012): 026107(8). https://doi.org/10.1103/PhysRevE.85.026107; Wandelt et al., "A Comparative Analysis of Approaches to Network-Dismantling."
39. Wandelt et al., "A Comparative Analysis of Approaches to Network-Dismantling."
40. David Aaron, *In Their Own Words: Voices of Jihad*, 1st ed. (Santa Monica, CA: RAND Corporation, 2008).
41. Ibid, 302.
42. Vidino, "Radicalization, Linkage, and Diversity," 99–118; Bonnie H Erickson, "Secret Societies and Social Structure," 188–210; Krebs, "Mapping Networks of Terrorist Cells," 43–52.; ICCT, "The Foreign Fighters Phenomenon in the European Union"; Baker et al., "The Social Organization of Conspiracy," 837–60; Richardson, *What Terrorists Want: Understanding the Enemy, Containing the Threat*; McAdam et al., *Dynamics of Contention*; Donatella della Porta, *Clandestine Political Violence*; Kriesi, "Political Context and Opportunity," 67–86.
43. Ibid, x.
44. The logic behind this specific targeting is related to the point made previously, i.e. that these individuals had the most grievances and were thus more susceptible to radicalization. As such, the members of this network were not so much radicalized Islamists, but rather Islamicized radicals.
45. Marc Sageman, *Leaderless Jihad: Terror Networks in the Twenty-First Century* (Philadelphia, Pennsylvania: University of Pennsylvania Press, 2008); see also Neil J Smelser, *The Faces of Terrorism: Social and Psychological Dimensions*, 1st ed. (Princeton, NJ: Princeton University Press, 2009); Kalyvas, "'New' and 'Old' Civil Wars: A Valid Distinction?," 99–118; Scott Atran,

"Genesis of Suicide Terrorism," *Science* 299, no. 5612 (March 7, 2003): 1534–39. https://doi.org/10.1126/science.1078854.
46. Marc Sageman, "The Turn to Political Violence in the West," in *Jihadi Terrorism and the Radicalization Challenge: European and American Experiences*, edited by Rik Coolsaet (Abingdon, Oxon: Routledge, 2011), 127.
47. An example of this is promoting democracy abroad to combat terrorism. See e.g. Sageman, *Understanding Terror Networks.*
48. Krebs, "Mapping Networks of Terrorist Cells," 43–52.
49. Rodriguez, "The March 11th Terrorist Network: Its Weakness Lies in Its Strength."
50. Koschade, "A Social Network Analysis of Jemaah Islamiyah," 559–75.
51. Gutfraind and Genkin, "A Graph Database Framework for Covert Network Analysis."
52. See e.g. Xu and Chen, "The Topology of Dark Networks," 58–65.
53. To clarify, Abaaoud had been to Islamic State territory three times and had formed many connections, while Abdeslam had never been there.
54. Holme et al., "Attack Vulnerability of Complex Networks."