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EXPLORING THE FACEBOOK NETWORKS OF GERMAN ANTI-IMMIGRATION GROUPS

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Chapter I - Introduction

I am writing this introduction in the summer of 2019. In my home, Berlin, this year is a special one, as we commemorate the 170th, the 100th, and the 30th anniversaries of three German revolutions. On my daily commute through the city, I pass some of the places that epitomize each of these upheavals: a graveyard reminds us of the fights on the barricades that marked the outset of the 1848/49 revolution, while the violent death of the Spartakists Karl Liebknecht and Rosa Luxemburg in 1919 is remembered with a plaque on the Landwehrkanal, and a line of cobblestones throughout the city indicates the Berlin Wall that fell in 1989. But what I also see along the way are the signs of contemporary, smaller, struggles, graffitied to the walls, placarded on mailboxes, and hanging from the windows of squatted houses. “Seenotrettung ist kein Verbrechen”[1] or “Asyl ist Menschenrecht”[2] but also “Enteignen!”[3] or “Bezahlbaren Wohnraum für Alle”[4]. While public displays of contention have surely been part of the protest repertoire during the revolutionary events of the 19th and 20th century, there is a tiny, but significant 21st century addition, that symbolizes the initial puzzle which sparked my interest in this topic, culminating in this dissertation: four lines, two horizontal ones, and two vertical ones crossing rectangular. The hash sign #, pointing each passer-by to the right keyword on the social media platform Twitter. While surely, media have played significant roles prior to digitalization, the ubiquity of digital communication and the alterations of the public sphere brought about by it, indicate a specificity of the protest and collective action phenomena of our time, that

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[1] “Sea rescue is not a crime”
[2] “Asylum is a human right”
[3] “Expropriate!”
[4] “Affordable housing for all”

has drawn substantial scientific attention and continues to do so. However, this scholarly attention has come from different disciplines with different perspectives and conceptualizations, and various studies have come to very different conclusions on the role information and communication technology in general and social networking sites in particular play for collective action. Chapter II will discuss in detail how early enthusiasm on the almost causative relationship between technology and social change has waned to make room for more skeptical perspectives, illustrating the need for further research and the systematic assessment of the use of digital communication tools in various episodes of collective action. For me, the ubiquity of social networking sites in collective action phenomena and their unclear role therein is the first important motivation of my own research.

The second motivation lies in a more sinister observation: the resurgence of the political right in Germany in general, and of anti-asylum-seeker protests in particular. While the slogans cited above surely represent the feelings and attitudes of many citizens in the inner-city of Berlin – where leftists and greens secure comfortable majorities at the polls – we must not look far to find areas where the right-wing party Alternative for Germany is able to gain most of the votes and where the graffitis on the wall read “Asylflut stoppen”[5], or “120dezibel”[6]. After a wave of violence and arson-attacks on asylum shelters and houses of migrants in the early 1990s, culminating in the murder of five women and children in Solingen, the relatively peaceful years that followed were ended abruptly by a dramatic rise in anti-immigration protest and a resurgence of politically motivated violence against asylum-

[5] “Stop the flood of asylum-seekers”

[6] “120 decibels” – A femonationalist campaign initiated by the Austro-German right-wing extremist “Identitarian Movement”

shelters from 2013 onwards. In general, we had to witness a fundamental change in the political landscape in recent years. The electoral success of right-wing parties all over Europe, the discovery of neonazi-terror-organizations like the Nationalsozialistischer Untergrund (NSU) in Germany, or the revelation of far-right networks entitled “NSU 2.0” run by German police officers on the WhatsApp communication platform, are exemplary evidence of strong right-wing structures in contemporary society that threaten democratic processes and values. Recently, the murder of the conservative politician Walter Lübcke has tragically illustrated these worrying developments. Lübcke spoke out in favor of an asylum-shelter in the Hessian town of Lohfelden and has ever since been targeted with death-threats (also) via social media like Twitter and Facebook. Eventually, he was murdered in his home by an alleged neonazi. In chapter III, we will illustrate the assumption of a resurgence of the political right in general and existing research on right-wing online networks in more depth. It suffices to say at this point, that the conjunction of a rise in right-wing activity and the massive use of social networking sites by these actors form the problematic backdrop of my research.

Based on these observations, my thesis aims to contribute to a better understanding of the role of social networking sites for collective action, particularly on the little-studied but highly relevant extreme right end of the political spectrum. Thus, to place this dissertation within a stream of broader academic debates, we can pose the following, overarching research question: What is the role of Information and Communication Technology for contentious grassroots organizations? This question feeds from a review of relevant theoretical angles and prior research that will be presented in chapter II. We will seek to contribute to this debate from a genuinely relational perspective on collective action, by subjecting the case of German anti-asylum-shelter (AAS) groups on Facebook to an in-depth theory-driven exploration. This way, I hope both to advance theoretical debates on information and communication technology and collective action by joining different streams of literature and to add substantial knowledge on the phenomenon of AAS-protest in Germany. To do so, I will rely on a modification of the framework of Modes of Coordination (MoC) of collective action, developed by Mario Diani (2015). This will allow for a systematic empirical exploration of actors and the structures that emerge from their patterned interactions, while at the same time avoiding the fallacy of equating any episode of contentious collective action with a social movement. Chapter II will concentrate on this and other theoretical challenges to argue for a perspective that unites action logics, Modes of Coordination, and partial organization concepts. After introducing the case under investigation more thoroughly in chapter III, I will present four detailed sets of research questions and introduce both the data-sets and the methodological tools that will be used to answer these questions. These will lend structure to chapter IV, where I will *firstly* analyze both online and offline activity patterns of AAS-protest across time and space. This section generates answers to the first set of research questions, which ask for an identification of the relevant actors and the correspondence of various on- and offline activities over time and space. *Secondly*, I will analyze the content of AAS-groups' communication by means of topic models. This is motivated by the second set of research questions, which ask to describe the actual content of AAS-discussions, especially in light of the construction and reinforcement of collective identities. *Thirdly* and *fourthly*, we will move on both to descriptive and to inferential techniques of social network analysis. These analyses seek to answer the research questions of set three and set four, which aim to understand the types of ties generated by AAS-groups' activities and the networks that emerge from these, as well as how these ties combine into Modes of Coordination and what determinants might facilitate tie formation in either mode.

With this, I present an innovative approach of analyzing and interpreting digital communication data from a perspective of relational social movement studies. The conclusions that can be drawn from this analytic approach will be discussed in chapter V, especially in light of the limitations of this study and how these shortcomings can be addressed in further research.

Chapter II - Theoretical Framework

The overarching topic of my research project is the role of social networking sites (SNS) for anti-immigration groups. Conceptually, the project taps into theoretical arguments from studies of collective action, digital media, and organizational scholarship to allow for an empirical exploration of how and why actors digitally coordinate their interactions and what different structures emerge from these activities. Therefore, I start by illustrating the controversial debate that surrounds the role of Information and Communication Technology (ICT) for collective action, before moving towards an in-depth understanding of collective action from a relational perspective. Next, I will examine the conceptual challenge of social media to collective action, before proposing to apply the Modes of Coordination framework (Diani 2015) to a study of digitally mediated protest phenomena, as one possibility to overcome theoretical gaps and misunderstandings.

II-i Information and Communication Technology and Collective Action – a Misunderstanding?

The key controversy driving the rationale of my approach is that of the unclear role of ICT in the formation of (contentious) collective action. The early confusion on that matter is best exemplified in the heated debate between Malcom Gladwell and Clay Shirky (2011). A fierce critic of social media's role in social change, Gladwell paraphrases African-American artist Gil Scott-Heron, claiming "*The revolution will not be tweeted*" (Gladwell 2010), because the kind of political action sparked by SNS is fundamentally different from 'classical' political activism that is more likely to bring change to society. The high-risk and high-cost nature of the activism during the

American civil rights movements in the 1960s (McAdam 1986; Tilly and Tarrow 2015), Gladwell argues, is key to the effectiveness of collective action, that simply cannot be provided by a social media sphere that mainly revolves around the question "*who is eating whose lunch*" (Gladwell 2010). The adverse, namely a low-risk and low-cost "*slacktivism*" is described as "*feel-good online activism that has zero political or social impact*" (Morozov 2009). Or, as Christensen (2011) sums up the critics' arguments:

> *Wearing badges is not enough, and neither is changing your profile picture on your Facebook account for a day, a week, or a month. The slacktivists are seen as unwilling to get their hands dirty and do the efforts required to actually achieve these goals*.

The nature of online networks, critics argue, is one of "*weak ties*" of a Granovetterian (1973) notion, and not of strong ties as in McAdam's argument. Geographer Walter Nicholls (2009: 79) however hints at the interplay of strong and weak ties in social movement mobilizations:

> *strong tie relations provide a distinctive set of resources (emotional, material and symbolic) that are essential for successful mobilisations. In this sense, the weaker connections of distant allies and the stronger ties of their proximate counterparts permit the flow of distinctive yet complementary resources.*

In his view, ICT or the internet serve as both facilitators of more distant and weaker ties, but they also serve to sustain and maintain stronger, more proximate interpersonal ties. Still, for critics of ICT, it is clear that Computer Mediated Communication (CMC) is effective in establishing flows of information and new ideas – however, these are regarded as weak ties and insignificant for collective action outcomes, whereas the strong ties of interpersonal solidarity are necessary to engage in collective action of the high-risk type.

Further critique stems from the often acclaimed, but seldom proven assumption of a lack of hierarchies, due to the networked nature of SNS (González-Bailón and Wang 2016). Referring to Morris' (1984) seminal work on "the Origins of the Civil Rights Movement", Gladwell (2010) argues that hierarchic organization is superior to networks in terms of outcome, as the involvement of the Church as a coordinating institutional actor in the civil rights movements illustrates. According to this critique, resilience and flexibility of networks are advantageous only in low-risk situations, while the strong ties in McAdam's argumentation can only be the product of non-network forms of organization, best achieved by traditional formal organization.

Countering the harsh critique, Clay Shirky (2011) argues that

> *as the communications landscape gets denser, more complex, and more participatory, the networked population is gaining greater access to information, more opportunities to engage in public speech, and an enhanced ability to undertake collective action*.

He cites the loose coordination of mass protests via text messaging that eventually led to the downfall of Philippine President Joseph Estrada in 2001 as one example how ICT can bring about social change. Certainly, the "*Twitter Revolutions*" of 2011 (Lotan et al. 2011) and the *Occupy* campaigns made it easy for these "*cyber-optimists*" (Pavan 2013:3) or, in Evgeny Morozov's words: "*cyber-utopians*" (Morozov and Johnson 2013), to subscribe to the idea that with the advent of social media, "*we now have many-to-many tools that support and accelerate cooperation and action*" (Shirky 2008:158). The role that social media plays for civic and political participation in general has been summed up in a meta-analysis by Shelley Boulianne (2015), who found that while most studies report positive effects of social media use on participation, the causal and transformative effects remain unclear. For contentious political activities, she concludes that it is still "*difficult to isolate the relationship between social media use and protest*" (Boulianne 2015: 534). In an earlier summary of ICT and collective action, Mosca (2008: 2) argues that the internet creates *"new public spheres where social movements can organize mobilizations, discuss and negotiate their claims, strengthen their identities, sensitize public opinion and directly express acts of dissent"*. Thus, as scholars of the public sphere have highlighted, new forms of communication do not lead to some or another form of action or protest *per se*, but rather change the conditions under which political communication plays out in a more than ever *networked* public sphere (Benkler et al. 2015; boyd 2010; Friedland, Hove, and Rojas 2006). From this perspective, Dahlgren argued that

> *the current destabilization of political communication systems must be seen as a context for understanding the Internet: It enters into, as well as contributes to, this destabilization. At the same time, the notion of destabilization can also embody a positive sense, pointing to dispersions of older patterns that may have outlived their utility and possibilities for reconfiguration. We can note, for example, the obvious positive consequences that the Internet extends and pluralizes the public sphere in a number of ways. It is this kind of tension that I would accentuate, rather than any cheery optimism, dour pessimism, or cavalier dismissal* (2005:148).

In this view, the relation between social media as one relatively new communication tool and any form of political engagement is by no means deterministic. This, however, is the notions that cyber-optimists imply, even when they argue that *"social tools don't create collective action – they merely remove the obstacles to it"* (Shirky 2008: 159), these arguments ultimately entail the notion that tools shape behavior, and revolution "*happens when society adopts new behaviors*" (2008:160).

While this heated debate can be fueled by ample empirical hints on both sides, little consensus seems in sight. Or, as Christensen put it:

> *while techno-utopians overstate the affordances of new technologies (what these technologies can give us) and understate the material conditions of their use (e.g., how factors such as gender or economics can affect access), techno-dystopians do the reverse, misinterpreting a lack of results (such as the failure of the Iranian protesters to topple the Ahmadinejad regime) with the impotence of technology* (2011:239).

Thus, whether social media breeds "*slacktivism*" (Morozov 2009), "*micro-activism*" (Blood 2001; Marichal 2013), or "*Revolutions 2.0*" (Cocco and Albagli 2012) will remain contested, as some of the more popular (and sometimes populist) debate quoted so far lacks the conceptual tools to find common intellectual ground for a thorough debate of what social media can and cannot contribute to our understanding of collective action phenomena. I identify three major fallacies of oversimplification in the debate so far that each should and can be avoided in future research.

First, the focus on the *output* of social media in studies of collective action may be misleading, as it entails the notion of social media as a black box that has some overall direct or indirect effect on the offline nature of contentious collective action. The impact of (social) media on political participation in general, has long been an issue of debate, concern, and ambiguity in various scientific disciplines (Boulianne

2015; Norris 2001, 2005; Putnam 2000). While Norris suggested that *"the rise of the knowledge society in Europe has indeed had the greatest positive consequences for politics by strengthening cause-oriented and civic-oriented activism, rather than by encouraging mass participation in campaigns and elections*" (2005:35), Bimber studied the impact of internet usage on various forms of political engagement, finding little evidence of an instrumental relationship between ICT and political participation. He concluded that researchers should focus on

> *examining how information technology affects attention, salience, affect, schema, and other cognitive phenomena involved in the formation of political knowledge. If information technology is to affect political participation, it will likely be through such pathways rather than through simple reductions in cost or increases in the volume of political information* (2001: 64).

This runs contrary to an over-simplistic technological determinism that would make us believe that reducing costs of participation and mobilization, while providing the technological affordances to share real-time information, is per se sufficient to explain any form of activism. Instead, more attention needs to be paid to what actually *happens* on social media. While it is easy to find instances of online activity that correlate with protest or other forms of collective action, the same is true for the opposite. We can observe that the massive use of ICT during some protest campaigns played a significant role, but at the same time find instances where collective action has happened and continues to happen in the absence of ICT (Diani 2011; Diani 2000; Tilly and Tarrow 2015). Therefore, while quantifying a sort of "net effect" of social media on outcomes remains tempting from the perspective of some scientific schools, I argue that we must first take a step back and untangle the "black box", rather than treating the absence, presence, or quantity of digitally mediated communication as a mere property of a phenomenon we would like to study. Or, as Bimber (2017: 7) put it: "*Media are a seamless part of many people's life experience rather than a discrete tool or set of tools whose use can meaningfully be isolated, quantified, and correlated with other aspects of life*". Therefore, adopting a relational approach allows for a "*systematic network mapping*" (Diani 2015, 5) to study "*the variety of relational patterns taken by collective action, regardless of its media*" (Diani 2015, 11). When studying digitally mediated protest phenomena, such an approach must invariably start with a mapping of *"the actors that enter the space of the mobilization through services like Facebook, Twitter or YouTube; the connections that they establish with other platforms' subscribers; the contents that are produced or remixed and their patterns of circulation"* (Pavan 2013: 5). This allows us to understand the different ways, media is used by (contentious) actors, the meaning of digitally produced and/or sustained connections, and the patterns and configurations that ultimately evolve through acts of communication.

Second, and closely related to the first argument, the controversy outlined above fails to properly account for the complexity of the offline-online nexus. Debating if any form of online activity has a one-directional impact on or is even causative of offline activity (Müller and Schwarz 2018) fails to acknowledge the dynamic, reciprocal, and hybrid nature of offline and online spheres. In a study of protest participation in Tahrir Square, Tufekci and Wilson (2012), found that information flows during protest events depended on a mix of both digital and analogue interpersonal communication, via face-to-face conversation, the telephone, and Facebook. The activities around Occupy Wall Street serve as a good example for avoiding the online-offline dichotomization-fallacy. Tilly and Tarrow noted, "*it is striking how closely the beginning of actual Occupy sites was matched by the creation of Occupy-linked websites*" (2015: 220). This co-occurrence of online and offline action is (of course) not seen as independent of each other, but neither is the one causing the other. Or, as Vasi and Suh, who studied the diffusion of Occupy in depth, argue:

> *Our findings, however, do not demonstrate that Facebook or Twitter activities cause the protests. Instead, we argue that social media activities precede and correlate with the emergence of protests, presumably because they are both consequences of a third "unobservable" variable: the presence of energized activists (2016: 150).*

They argue against any form of determinism and concede that while social media may facilitate phenomena such as "slacktivism", they did not observe this form of action empirically – instead, online platforms seemed to enrich the toolbox available to activists in terms of communication, coordination, and mobilization. In other words, it seems unlikely that the use of ICT leads to a "crowding-out" effect of street activity. Instead, in the Occupy case, it seems more likely that activists already held certain *organizational resources* like informal networks, that allowed them to make effective use of strategies within the entwined space of both on- and offline action (ibid.: 150-151). Thus, we might characterize the online and offline realm not as separated, but as a *hybrid* space, in which the affordances of social media may lead to a convergence of the activities of institutions, parties, and social movement actions in their common adaptation of both "*traditional*" and *"digital network repertoires"* (Chadwick 2007; see also Bimber, Flanagin, and Stohl 2005). The idea of "repertoires of contention" as a toolbox of practices and actions (riots, strikes, occupations, petitions, etc.) available, known, and familiar to contentious claim-makers has been conceptualized by Charles Tilly (1977), who studied changes in this repertoire in light of the emergence of capitalism. Recent research has shown how ICT can enrich this repertoire, e.g. how the appropriation and conversion of a police Twitter-hashtag to document violence against minorities (Jackson and Foucault Welles 2015) can go hand-in-hand with street-protests, political lobbying and other more traditional forms of action. This case has been argued in the Black Lives Matter movement (Freelon, Mcilwain, and Clark 2018), anti-deportation (van Haperen, Nicholls, and Uitermark 2018), or anti-free trade protests (Ayres 2005), showing that a repertoire perspective is one way of recognizing the hybridity of online and offline-spheres.

Thus, given the multidimensionality of a collective action field, it is the *"structure of relations supporting collective action that expands across the boundary between the online and the offline"* (Pavan 2013). In his study of the uprising in Egypt, Hassanpour found out that shutting down ICT during an ongoing protest *"decentralized the rebellion on the 28th*[7] *through new hybrid communication tactics, producing a quagmire much harder to control and repress than one massive gathering in Tahrir"* (2014:10). While capturing the hybridity of online and offline empirically remains a different challenge, it is important at this point to conceptualize a hybrid space where actors constantly move across online-offline boundaries and shift their repertoires according to perceived opportunities and challenges. Therefore, studying which actors are involved, how they interact, and which relational patterns emerge and

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[7] The day the Mubarak regime massively interfered with cell phone and online communication. [M.H.]

eventually form different *"Modes of Coordination"* (Diani 2015) can lead us away from a flawed and overly simplistic cause-effect relation of online and offline. This can help to avoid the fallacies of either overstating or downplaying social media's role in collective action.

Third, the debate suffers from a lack of precision in its terminology. The reference to Twitter "*revolutions*" (Rheingold 2003; Lotan et al. 2011), be it critical or enthusiastic, and the common usage of the category of "(social) movement" when describing very different collective action phenomena (Castells 2015; Stier et al. 2017), does little to help analytic precision. A quick look at Thompson and Reuters "web of science" reveals that the yearly number of scientific articles with the terms "social media" and "social movement" in the title has risen from 2 in 2011 up to 34 in 2017, and yearly articles with just the terms "social movement" in the title have more than doubled from 134 to 328 during that time. The growing scholarly attraction to these issues, in combination with an increased interest outside of the fields of sociology and political science (Bakardjieva 2015; Mattoni and Treré 2014), can come with the risk of ambiguity in the usage of key concepts and definitions and hence lead to terminological confusion. In recent publications, we find the category of "social movement" applied to very different phenomena, such as 'Against Modern Football' (Canniford, Millward, and Hill 2018), 'One Day One Juz' (Nisa 2018), PEGIDA (Stier et al. 2017), '20 cents' (Soares and Joia 2018), 'Black Lives Matter' (Freelon et al. 2018; Mundt, Ross, and Burnett 2018), or the 'Sunflower Movement' (Yang and Hsiao 2018). Whether or not these phenomena are actual social movements by one or another definition is not for me to decide and is not the interest of this work. Instead, it serves as a mere illustration of the broad (and at times unquestioned) usage of this category and the need for precise terminology and typology in analyses. To tie this back to the popular debate sketched above, we may now better understand the "slacktivism"/" twitter revolution" schism: put simply, the role we accredit to ICT or SNS for collective action in parts depends on our understanding of key concepts like social movements. While I will discuss these concepts in more depth in the next section, it suffices to say here that this study will follow a view of social movements as one "*distinct analytic category*", as elaborated by Diani (1992, 2015).

Again, a focus not on the mere absence or presence of social media activity, but instead on the way actors use social media and on the patterns that evolve with this usage, can help us towards a more clear-cut categorization. Or, as Pavan put it:

> *the asset to collective dynamics is not the mere presence of vast and easily accessible digital networks. In fact, it is the conscious and strategic effort made by social actors to shape and use these networks as spaces for political participation, as strategic communication venues to connect and remix heterogeneous competences, experiences, and skills and, in this way, to broaden and accelerate the formation of new collective meanings, frames, and action strategies to challenge the status quo* (2017:435).

On the one hand, denouncing any form of political online activity as slacktivism does forget that very different actors enter the social media space with very different objectives and strategies in mind. One the other hand, invoking the notion of a social movement for each highly shared hashtag on social media is equally misleading. Therefore, carefully examining the multiplexity of exchanges and the various relational patterns that do or do not emerge from these exchanges is a more feasible perspective, allowing the separation of short instances of mass-participation from sustained social movements. With this argument, I follow Diani, who proposes to test the theoretical framework of Modes of Coordination in the study of online interactions, suggesting

> *that a more diversified set of concepts such as those offered by the typology of Modes of Coordination presented here would reduce some of the ambiguities of the current formulations, keep us away from potentially misleading uses of categories such as "social movement", with all the implicit assumptions and expectations that the term carries, and enable us to focus on the important challenges that those studies identify* (2015: 214).

In the remainder of this chapter, I will seek to outline a path toward a theory-driven exploration of online protest activity by discussing a relational perspective on collective action (section II-ii), the theoretical challenges that come with the emergence of SNS (section II-iii), and the way concepts like informal organization (section II-iv) and Modes of Coordination (section II-v) help to understand digitally mediated protest phenomena.

II-ii Relational Perspectives to Collective Action

Collective action was defined by Alberto Melucci as

> *a set of social practices (i) involving simultaneously a number of individuals or groups, (ii) exhibiting similar morphological characteristics in contiguity of time and space, (iii) implying a social field of relationships and (iv) the capacity of the people involved of making sense of what they are doing* (1996:20).

In this understanding, which Melucci himself called "*minimal*" and "*most general*" (ibid.), he was trying to bridge a European tradition of a focus on collective identity and the processes that shape collective action (Touraine 1985) and an American tradition of a resource mobilization approach (McCarthy and Zald 1977). A key argument Melucci makes is the call for analytic criteria "*which enable us to make more specific distinctions within the general category of collective action*", asking "*what is it that authorizes us to talk of social movements as sociologically specific phenomena*" (1996:19). This means shifting the analytical focus in collective action studies toward exploring "*how it is produced, and disassemble its unity so as to reveal the plurality of attitudes, meanings, and relations that come together in the whole of the phenomenon"* (1996:20). Disassembling empirical phenomena that are easily dubbed "social movements" or even "revolutions", means shifting away from a perception of unity of a phenomenon towards analyzing the social processes, interactions, and outcomes, that make up our objects of study. In fact, when looking at some key definitions of social movements, it becomes clear that they are better used to define specific social phenomena, rather than serve as broad umbrella categories for any form of collective behavior. Sidney Tarrow defines social movements as *"collective challenges, based on common purposes and social solidarities, in sustained interaction with elites, opponents, and authorities"* (2011:9) and as *"sequences of contentious politics based on underlying social networks, on resonant collective action frames, and on the capacity to maintain sustained challenges against powerful opponents"* (ibid.:7). For Tarrow, these definitions manifest in four distinct empirical traits: *"collective challenge, common purpose, social solidarity, and sustained interaction"* (ibid.:9). Diani offers another definition: *"A social movement is a network of informal interactions between a plurality of individuals, groups and/or organizations, engaged in a political or cultural conflict, on the basis of a shared* *collective identity"* (1992:13). With different emphasis, both definitions share the aspects of conflict, challenge, and contention, of shared collective identity, solidarity, and framing, and of interaction in networks. The key point for this thesis is not one of an in-depth discussion of social movements, but rather the conclusion that social movements may be one manifestation of a broader analytic category: collective action. Therefore, rather than applying the "social movement"-label a priori and invoking certain expectations (see the previous section), these perspectives urge us to empirically study the properties of a phenomenon in order to come to a classification of what exactly we are looking at. Contentious collective action is vital for Tarrow's understanding of social movement, but contention and conflict are not necessarily aspects of collective action per se. In fact, he argues that *"collective action can take many forms – brief or sustained, institutionalized or disruptive, humdrum or dramatic"* (2011:7), which may include *"voting and interest group affiliation to bingo tournaments and football matches"* (ibid.:9). *"But these"*, he concludes, *"are not the forms of action most characteristic of social movements"* (ibid.:9).

Thus, this line of scholarships informs my approach in the sense that it tries to avoid invoking unjustified expectations by overstating the relationship between social media and collective action a priori. Instead, the aim is a careful observation of the way different actors use SNS and come to a theoretically grounded empirical typology of interaction patterns. The idea to study *how* actors make sense of their actions resonates strongly both in framing perspectives to collective action (Benford and Snow 2000; Snow 2004), and in relational sociology (Crossley 2011, 2013, 2015; Mische 2011). The latter, Fuhse (Fuhse and Mützel 2011) describes as a cultural turn in the study of networks. He argues, that relational sociology tries to overcome a strict structuralist approach that *"reduces social phenomena to the pattern of relations, with systematic disregard for everything else – cultural imprints, individual motivations, and institutional frameworks"* (Fuhse 2015: 15). The works of White (2008) or Emirbayer (1997) argued that "*social networks are fruitfully studied in conjunction with culture, rather than in abstraction from it*" (Fuhse 2015:15).

Relational approaches to the study of *collective action* (Krinsky and Crossley 2014; McAdam and Diani 2003) thus highlight the both material and symbolic opportunities and constraints (della Porta and Diani 2015) of the patterned interactions that make up the structure of social networks. These constraints and opportunities of a network are "*simultaneously exposing them [actors] to and insulating them from various influences*" (Crossley 2013). Diani explicitly contrasts between "*aggregative*" and "*relational*" approaches to social structure, whereas the former perspective views "*structure as the sum of the properties of its discrete components*" (Diani 2015: 2). He argues that research on collective action processes or social movements from an aggregative perspective describes individual actors, organizations, or events in terms of their traits or properties, where changes in the structure or the outcome of a movement reflect changes in the distributions of properties among actors. This "*reductionist view*" (2015: 2) would thus interpret the relationship between actor A and actor B as a property of one or both actors. This, he argues, is less due to a theoretical difference between both approaches, but rather due to data availability and conceptual decisions in the design of empirical work. Overcoming a purely aggregative approach and moving towards an integration of a relational perspective requires shifting the focus of analyses towards studying "*how actors carrying different* *traits and orientations link to each other in distinctive structural patterns*" (Diani 2015: 4).

The idea of conceptualizing society as inherently relational goes back to Simmel's (Simmel 2013) notion of the 'intersection of social circles' and Moreno's operationalization of this idea, and has taken hold in the study of collective action in the last twenty years (Eggert and Pavan 2014). A shift towards a different unit of analysis, meaning "*the network of social relations and interactions between actors*" (Crossley 2012: 1), can allow for a better and more accurate description of social life in contemporary society and account for both structure and agency. Therefore, I argue that techniques of Social Network Analysis (SNA) can be instrumental to understanding collective action, as SNA offers an ever-advancing methodological toolbox to understand collective action. Mapping actors and their multiplex interactions allows insights into who enters the scene, which alliances are formed or not formed and how collective meaning may be produced by repeated interactions. The typology of "*Modes of Coordination of collective action*" (Diani 2015) offers precisely the analytical lens to avoid a "mushrooming" of the social movement category of collective action but grasp empirical phenomena as distinct in their respective processes or boundary definition and resource allocation. Before we introduce these concepts and the guiding framework of my analyses in more depth in section five of this chapter, we will revisit the debate on ICT and collective action in a more systematic fashion. Therefore, the following two sections will seek to illustrate more recent and nuanced contributions to the debate that are focused on different logics of action and of organization. As such, they can offer important building blocks of a theoretical perspective that will hopefully circumvent some of the fallacies introduced in the beginning of this chapter.

II-iii ICT and Collective Action – a Challenge

Having introduced some of the developments in the debate on collective action and a relational perspective in particular, the question remains, why ICT and more particular SNS might be problematic in conceptual terms. Surely, academic controversy is hard to avoid, where different disciplines and intellectual traditions meet. Bakardjieva (2015) pointed out, that the importance of social media in recent protest campaigns suddenly put the communication sciences in the center of a field of study, traditionally shaped by sociology and political science. Especially for scholars of communication, 'traditional' collective action theory fails to properly account for digital communication technologies, as

> *an array of actions*[8] *in which technologies of information and communication are central has proven theoretically and empirically intriguing from a collective action standpoint. Self-organizing online groups, rapidly assembled networks of protesters, "meet ups," new structures for interest groups, and "viral" e-mail lists are all examples of collective behaviors employing advanced communication and information technologies* (Bimber et al. 2005:365–66).

[8] Among the many studies produced on these phenomena, I want to mention examples of social media used both for protest mobilization, as in the case of the Indignados protests in Spain (Anduiza, Cristancho, and Sabucedo 2014; Theocharis et al. 2015), as well as for collective identity processes, as in the Occupy campaign (Kavada 2015).

One of the key controversies lies in the role of (formal) organization(s). Scholars who advocate the concept of "*networked social movements*" (Castells 2004, 2015) argue that the advent of the internet, this "*network of networks*" (Hall 2011) fundamentally alters the way, social movements may mobilize, meaning they *"ignored political parties, distrusted the media, did not recognize any leadership and rejected all formal organization, relying on the Internet and local assemblies for collective debate and decision-making"* (Castells 2015:4). Castells argues, that interaction through new communication tools creates flat hierarchies, more participation, and less formal organization, as traditional gatekeeping-mechanisms can be circumvented via the direct interpersonal, yet public communication via social media. This, he concludes creates a new *"species of social movement"* (ibid.:15). In the new *"individualized publics"* (Bennett and Segerberg 2013), social processes and technological innovation create conditions under which substained mobilizations may happen without the previously necessary levels of collective identity and organizational resources (ibid.). In their influential work on the *"logic of connective action"*, Lance Bennett and Alexandra Segerberg (2012, 2013) argue that organization in collective action may result from massive engagement in communication as *"personalized paths to engagement"* (Bennett and Segerberg 2013:2). Thus, even in the absence of formal organizations like churches or labor unions, a crowd connected through digital media platforms can provide similar organizational functions. The networks that result from communication processes are thus: *"individualized and technologically organized sets of processes that result in action without the requirement of collective identity framing or the levels of organizational resources required to respond effectively to opportunities"* (Bennett and Segerberg 2012: 750). Bennet and Segerberg contrast this ideal type of the “logic of connective action” with another ideal type of a modernist, rational choice based “logic of collective action” as assumed in the work of Mancur Olson (1965), which formulated collective action problems in terms of free-riding and the strength of formal organization. When following a definition of collective action as a *“range of social phenomena in which social actors engage in common activities for demanding and/or providing collective goods”* (Baldassarri 2009), it becomes clear why mobilization for and participation in collective action is problematic from a rational-choice logic. It means that in such a logic, we would assume individuals to have little incentive to participate in collective endeavors that may not pay off directly or where rewards are unclear. Perceiving their own interests and identities as part of a collective struggle and joining formal organizations is costly and at times offers little returns – thus the question of overcoming these hurdles is key to conceptualizing an Olsonian logic of collective action. In this logic, another problem of achieving effective organization is the question of small or large numbers, where size may be an impediment. The key to overcoming collective action problems is formal organization as without it, organizational problems such as *“locating and contacting appropriate participants, motivating them to make private resources publicly available, persuading them to remain involved despite short-term setbacks and long-term risks, and coordinating their efforts”* (Bimber et al. 2005) might render efforts of collective action impossible or ineffective. However, scholars of “critical mass” have highlighted that it is rather an issue of sufficient social organization to get people to work together (Marwell and Oliver 1993), while others have highlighted the role of new communication technology offsetting the large numbers problem (Lupia and Sin

2003). Following the latter argument, Bimber cites events as early as the 1999 protests against the WTO meeting, the infamous "Battle of Seattle", as an example, in which

> *the genesis of the protests can be traced to an electronic mail campaign initiated eleven months before the WTO meetings, with a single message distributed by Public Citizens' Global Trade Watch. From that event through the street protests in Seattle, events had a self-organizing character independent of central planning and finance* (2003:117).

Admitting a wider range of tactics, strategies, and (digital) actions to the repertoire of collective action, it becomes possible to conceive of actors as fluid in their participation, meaning that individuals' decisions in providing public information on a Facebook page, engaging in online discussions that shape collective identity, coordinating protest events through services like Twitter, participating in protest marches, petitioning to governments are all contributions to a common good that might emerge from interactive communicative processes rather than from formal memberships in organizations. In other words, *"the creation of a second-order good, such as publicly accessible database or archive of a bulletin board system that can later be used to organize collective action can completely dissociate the decision to contribute from the collective action"* (Bimber et al. 2005:373). Applying these ideas to our case, we can think of examples like online archives of right-wing mobilization collected by watchdogs that are made easily available to a general public and circulated via social media. Using these information would in turn allow more "radical" actors the organization of protest events. Gathering this information, spreading it online, and using it to mobilize is not necessarily done by the same actors, thus requiring no binary choice of the individual to "fully" participate (e.g. by joining a formal organization) in all forms of action at all times[9]. The authors argue that traditional accounts of collective action is limited to conditions of firm private-public boundaries, while ICT have put individuals in a position to constantly cross the now porous public-private boundary. It is precisely this constant process of private-public transition via social media that allows for collective action to be no longer reliant on formal organization but instead be driven by dynamics of self-organization (Bimber et al. 2005). Similarly, we can read the arguments of Bennet and Segerberg (2012, 2013). Starting from the vantage point of post-industrialist societies, with an erosion of institutional loyalties and group membership (Putnam 2001, Bennet and Segerberg 2012), they constitute that social media change the mechanisms for organizing action toward what they call "*personalized action formations*". Thus, the ideal type at the other end of the spectrum, the "logic of connective action" is based on the self-motivation of individuals to contribute in networked exchanges with little need for formal hierarchical organizations as brokers of information. Or, as Bennett and Segerberg put it:

> *In this connective logic, taking public action or contributing to a common good becomes an act of personal expression and recognition or self-validation achieved by sharing ideas and actions in trusted relationships. Sometimes the people in these exchanges may be on the other side of the world, but they do not require a club, a party, or a shared ideological frame to make the connection. In place of the initial collective action problem of getting the individual to contribute, the starting point of connective action is the self-motivated (though*

[9] Especially the case of monitoring activities of right-wing actors, online activism is far from risk-free. This means that the argument by Earl et al. (2015), does not only apply to threats from (non-Western) authoritarian regimes, but also to threats from the fringes of the political spectrum within democratic societies.

> *not necessarily self-centered) sharing of already internalized or personalized ideas, plans, images, and resources with networks of others* (2012:752–53).

This *"digitally networked action"* (ibid.) does not necessarily require the levels of formal organization associated with resource mobilization arguments (McAdam, McCarthy, and Zald 1996; McCarthy and Zald 1977), nor a collective framing (Benford and Snow 2000), but rather *"personal action frames"* disseminated via digital technologies (Bennet and Segerberg 2012). The resulting fluid networks can hence *"operate importantly through the organizational processes of social media, and their logic does not require strong organizational control or the symbolic construction of a united 'we'"* (ibid.:748).

This way of conceptualizing action logics and the role of organization(s) in it, has drawn critique from Sidney Tarrow, who argued that the *"two generations of work that have moved students of collective action beyond Olson's microeconomic approach"* (2014:469) have indeed shown that personalized frames have become a part of the collective action debate even before massive digital communication tools. In a response to this point, Bennett argues that he and Segerberg use *"Olson only to construct a theoretical continuum bounded by two ideal-type logics of social association: rational choice assumptions about mobilizing individuals at one end, and self-motivated social networking at the other"* (2014:470).

Indeed, Bennett and Segerberg do comment on more recent developments in the literature that have highlighted culture, identity, networks, and opportunity structures (Koopmans 1999; Melucci 1996; Della Porta and Diani 2015; Tarrow 2011; Tilly 2015; Tilly and Tarrow 2015). However, they identify a "modernist logic" in these approaches, which highlight

> *the importance of particular forms of organizational coordination and identity in the attention given to organizations, resources, leaders, coalitions, brokering differences, cultural or epistemic communities, the importance of formulating collective action frames, and bridging of differences among those frames* (Bennet and Segerberg 2012: 750).

From this perspective, the necessity of formal organizations to broker relationships and disseminate content across members becomes obsolete in a logic of co-production and sharing. The initial collective action problem of getting individuals to participate does hardly exist, when self-motivated expressions are brought together on social media platforms. Or, in Bennet and Segerberg's words:

> *the technological agents that enable the constitutive role of sharing in these contexts displace the centrality of the free-rider calculus and, with it, by extension, the dynamic that flows from it – most obviously, the logical centrality of the resource-rich organization* (ibid.: 760).

Without picking a side in this debate, I want to highlight two key aspects of this exchange that can help avoid the fallacy of constructing a "collective action" vs. "connective action" dichotomy. First, the differences between connective and collective do not necessarily lie in the form of action, but in the underlying organizing logic behind it. Second, these concepts serve as *ideal types*, meaning that in every real-life episode of contentious collective action, we may very well observe a mix of different logics in place. Therefore, both dismissing the impact of ICT in the formation of a "*networked public sphere*" (Benkler et al. 2015; Dahlgren 2005) and of "*counterpublics*" (Downey and Fenton 2003) as nothing new and no different from other changes in technology, or overstating its impact by calling every instance of digitally mediated action an instance of "*connective action*" would be equally wrong.

Thus, instead of creating artificial oppositions, I believe it is worthwhile to highlight the commonalities of a relational approach to the study of collective action and approaches from the communication sciences that naturally emphasize the role of digital platforms. Most obviously, the scientific perspectives sketched in this section share the belief that networked interactions form the base of collective action and thus networks and the way they form, interact, and dissolve are the primary *objects* of study. As for the role of (formal) organization(s), we might have to move away from the ideal-types of formal, hierarchical organizations on one side, and the connected crowd on the other side. In the next section, I will look into contributions from the field of organizational scholarship that can help us conceptualize the middle-ground. To do so, we can take a look at the concept of "*partial organization*" or "*organization without organizations*" (Ahrne and Brunsson 2011) as the intermediary to allow for a nuanced and critical empirical investigation of social media's actual role in collective action processes.

II-iv Organization(s) Outside of Organizations?

By now, it should have become clear why some assumptions about collective action, its underlying logics and the role of ICT in it, can lead to the fierce debates outlined in the first section of this chapter - why one might be tempted to see Occupy, Indignados and the likes as ample evidence for a new age of collective action driven by social media or why one might be willing to dismiss social media as watering down collective action and producing mere slacktivism. The following sections however have outlined that more careful and nuanced empirical observations might be in order, which also means investigating the middle-ground between the opposing ideal-types sketched out above, to allow for a better integration of social media in our understanding of collective action.

Empirically, I propose an application of the Modes of Coordination framework to cases of online networks. This approach follows Pavan's (2014) call to shift the focus of study toward the internal dynamics of collective action networks mediated by ICT. If we can map different actors and different relational patterns in a dynamic way, it might become clearer which organizing mechanisms are actually in play and which are not. Formation and coexistence of different Modes of Coordination will allow us to understand how exactly actors use social media and what the driving forces behind the formation of networks are. Rather than bluntly accepting notions of flat hierarchies, leaderless self-organization without formal organizations, enabled by the agency of the medium itself, we should more carefully opt for a thorough exploration of the phenomenon at hand instead of chiming in with the choruses of cyber optimists or cyber pessimists (Eggert and Pavan 2014; González-Bailón and Wang 2016). This can be enabled by relaxing some conceptual assumptionson the nature of organization to find more fertile common soil. In a close reading of the connective action argument, Bakardjieva warns us of an oversimplified structuralism: "*media structuralism, the tendency to construe complex social and cultural phenoma as being produced by the inherent logic of a particular communication technology or medium*" (2015:985). Personalized action frames from Bennet and Segerberg's argument, do, in Bakardijevas reading, not necessarily mean that a user who feels empowered by the flows of social media content to 'do something', does not care about a collective 'we' in her decision to partake in action of any kind. She argues that when connective action is seen in opposition to *"stable identities, ideologies and organizations*" (2015: 986), this overlooks that collective identity in Melucci's (1996) understanding allows for a constant negotiation of identity in exchange with others, and is thus "*not incompatible with individual autonomy and personalization of expression*" (ibid.). In other words, there is no need to discard the 'collective' from action. The question is not whether or not a collective identity is negotiated in online communication, but "*how personal and collective identities and action frames interesect to produce collective agents with political efficiacy*" (ibid.). Conversely, she even argues that action, as opposed to behaviour, cannot be individual, but is collective in nature. Therefore, personalized action frames might well go hand in hand with the formation of the collective 'we' and 'they'.

This is well compatible with a sometimes overlooked aspect in the work of Bennett and Segerberg (2013), which is their own typology of the logics of connective and collective action as ideal types, enabling the conceptualization of three types of action (networks): "organizationally brokered", "crowd-enabled", and the hybrid "organizationally enabled" type. In Bennet and Segerberg's words: *"this form of organizationally enabled connective action sits along a continuum somewhere between the two ideal types of conventional organizationally managed collective action and relatively more self-organized connective action"* (2012:754, cf. Bennett and Segerberg 2013:46-48). The differences between these types lie in the role played by digital communication platforms, in organizing principles, in the role played by (formal) organization, the need for organizational resources and the need for frame alignment. In each empirically observable episode of (contentious) collective action, these types might overlap, interact, be in conflict and also change over time (ibid.).

Therefore, these arguments must not be read as a farewell to organizations, but rather as one perspective on the (changing) role of organizations in collective action episodes. For an exploratory study of anti-asylum online networks such as this one, these conceptualizations and their dynamic interplay in real-life can therefore be helpful to guide an investigation toward a meaningful interpretation of observations, grounded in perspectives of relational sociology, social movement studies, and insights from the field of communication studies.

When studying online networks, it may be hard to avoid the fallacies outlined in this chapter. Much controvercy exists around the role of organizations and since this is one crucial element to distuingish collective action types and episodes, I believe it is worthwhile to spend some brief time on the understanding of organization that I will apply in this study. After all, it becomes easier to find the right place for organization(s) on the conceptual table, when looking a bit more carefully at the concept itself. As we have seen, one focus of the critique of 'classical' collective action scholarship and the unfolding debate has been the role of the traditional Olsonian notion of the formal organization, with an understanding of formal and constant membership, hierarchical structures, and a common group identity. This somewhat overlooks developments in organizational theory itself. To be fair, even scholars of organization have seemed to loose interest in organization and shifted attention to institutions and networks, as Ahrne and colleagues note (Ahrne, Brunsson, and Seidl 2016). Defining organization as a "*decided social order*", Ahrne and Brunsson (2011) distinguish between complete and partial organization by the fulfillment of one or more of the five key criteria to organization: i) knowing who is involved and who is not by a sense of *membership*, ii) a shared understanding of what is done and how it is to be done by im- or explicitly formulating *rules*, iii) participants observing each other by decisions on *monitoring*, iv) the possibility to impose *sanctions,* v) knowing who has power and who does not have it by a sense of *hierarchy*. Ahrne and Brunsson argue against a notion of organization as full formal organizations, that are opposed to networks, which are fluid, non-hierarchical, and informal. They argue that this may be misleading, as "*there may be partial and even complete organizations in social situations that have been broadly described by some scholars as networks or institutions"* (2011:85). It may thus be tempting to take phenomena such as SNS and associate them automatically with a networked form of social order, without a closer empirical look of how order is produced within this network, meaning how ties emerge, information disseminates, if hierarchies develop and what patterns of exchange are actually observed among actors. This may overlook, that "*a social relationship that emerged as a pure network of individuals without any organization often gradually becomes organized with one or more organizational elements, thereby making relationships more visible both for those involved and from the outside*" (Ahrne et al. 2016). Thus, instead of an outright dismissal of the relevance of organizations for collective action in a networked society, we should relax the definition of organization away from the formal or "complete", toward a notion of partial organization. With that in mind Ahrne and colleagues argue that *"it is possible to dissolve the unproductive dichotomy between organization and network and instead investigate different uses of organizational elements*" (2016:98).

For this study, it is thus important to perceive of the groups whose online interactions I study, as partial organizations. Allowing for an understanding of collective action in which "*hybrid organizations*" (Chadwick 2007), formal organizations, partial organizations, or the crowd can each perform organizational functions, enables us to carefully and critically study their different roles, their interactions, and their relevance in each episode of contentious collective action. This may help to gain new insights about the nature of online collective action that can critically discuss the role of social media without overstating its role as causative or underestimating it as producing mere slacktivism. The analytic framework that I will apply in my study, enables us to map actors and interactions and allows for a typology of the Modes of Coordination of collective action to understand and analytically separate instances or episodes of collective action. While it has already been briefly introduced in this chapter, I want to spend some more sentences on the exact definitions of the two analytic dimensions and the four modes that will be operationalized in this study.

II-v Modes of Coordination of Collective Action

The key elements that make up the Modes of Coordination framework, are the two mechanisms of *resource allocation* and *boundary definition*, that allow for a typology of the four Modes of Coordination, namely the social movement mode, the subcultural/communitarian mode, the coalitional mode, and the organizational mode (Diani 2015, 2018), as illustrated in Figure II.1.

Before we illustrate this framework in detail, we may note that the underlying assumption of this approach is one that sees the civil society as an *organizational field*. One of the classic definitions given by DiMaggio and Powell sees the organizational field as the "*organizations that, in the aggregate, constitute a recognized area of institutional life*" (1983:148), while Scott defined the field as "*a community of organizations that partakes of a common meaning system and whose participants interact more frequently and fatefully with one another than with actors outside the* *field*" (1995:56 as quoted in Wooten and Hoffman 2008:130f.). While the first definition clearly stresses the (mutual and external) recognition of organizations in a field, the second one points toward internal ideological proximity and cohesion, by stressing shared meanings and interactions among field members. Both definitions thus simply stress various aspects of otherwise compatible positions, that can also be found in the characterization of fields in collective action scholarship, e.g. in Diani and Pilati's finding that "*organizational fields are characterized by organizations that recognize each other and are recognized under a same label*" (2011:278). By now, it should have become clear that this recognition is both a process and an outcome of networked interaction among field members, thus lending itself well to an analysis from a relational perspective. However, the notion of field is far from unanimous across scholars and disciplines, as Zietsma and colleagues (2017) have recently summarized. In their extensive review article, they draw a line between *exchange fields* and *issue-fields*, with the former more focused on collaboration among and between different populations of a general field, and the latter more focused on encompassing all organizations that hold stakes in a certain issue, regardless of actual collaboration and contrasting settings. In the example of our case, a view of "asylum" as an issue field would clearly also include migrants' organizations, as well as lot of organizations of the political left and the political right, who are unlikely to share meanings and values, or collaborate on specific issues. Nonetheless, these organizations are likely to identify each other as relevant in their field. However, coordination and joint mobilization among organizations is clearly placed in what Zietsma et al. called "Exchange Fields", or specifically "Social Movement Exchange Fields". These are comprised of populations of "*relatively homogeneous actors*" (Zietsma et al.

2017:396), which are "*more likely to share practices and norms, common meaning systems, and references to a common identity*" (ibid.). These fields "*exist to mobilize and coordinate actors and resources to further a specific agenda or extend an ideology*" (Zietsma et al. 2017:399). This resonates with what Fligstein and McAdam termed "Strategic Action Field", which they defined as "

> *a meso-level social order where actors (who can be individual or collective) interact with knowledge of one another under a set of common understandings about the purposes of the field, the relationships in the field (including who has power and why), and the field's rules* (2011:3).[10]

Clearly, the idea of a purposeful interaction rather than a mere aggregation of individuals and groups thus lies at the heart of exchange fields, rather than issue fields. From this perspective, it becomes evident why a relational perspective can focus on "*network patterns as a reflection of the logics through which actors in that particular field built their alliances and defined their identities*" (Crossley and Diani 2019:157).

Before we leave the general debate on fields and start illustrating how these organizational fields relate to Modes of Coordination of collective action, we may briefly pause and consider the applicability to our case. While the above examples have shown how the concept of a field may be stretched to fit various purposes, it is also clear that a focus on German Anti-Asylum-Shelter Groups does clearly not reflect a field of, say, "migration" civil society groups, or even of "anti-immigration" groups. Strictly speaking, we may thus rather look at a very distinct *subfield* or a homogenous *population* within a wider exchange field. Naturally, we may expect more

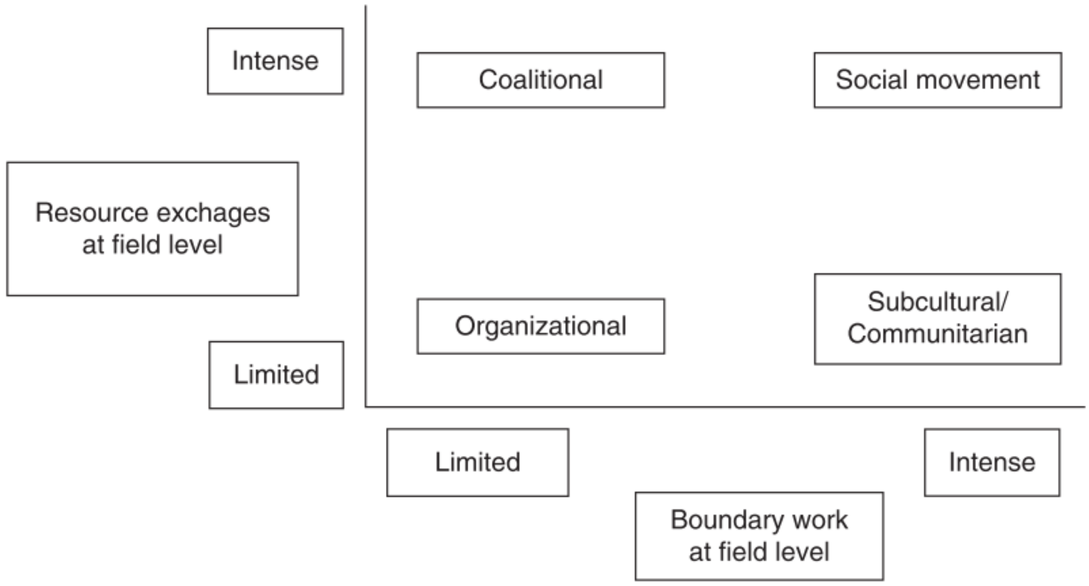
10 It must be noted however, that they explicitly did not take a social network perspective on the study of fields.

homogeneity and similarities among our population than in Diani's mapping of civil society in Glasgow and Bristol. Even more so, it becomes intriguing to test whether the Modes of Coordination framework may be scaled down to study the interactions of these members of a very distinct subfield. As we will see in later chapters, it will indeed be empirically shown that AAS-groups are connected to a wide array of other organizations through ties of recognition yet do tend to be significantly more connected amongst themselves.

In addition, Pavan has highlighted the difficulties to translate both the idea of organizational fields and of Modes of Coordination to the study of online networks, due to the "*inherent heterogeneity of online networks, where we are equally like to find meaningful contributions from individuals as from organizations*" (2015:913). However, Pavan also argues that in cases of "*hyperlink networks of organizational websites, the distance from Diani's approach is reduced*" (ibid). Since we have argued for an understanding of Facebook pages as partial organizations, and can also expect considerable homogeneity within our subfield, I believe that despite these difficulties and constraints, the case we are about to investigate nonetheless lends itself well to the conceptual framework we are about to use.

But before we come to its application, let us explain that framework a bit more: In his most comprehensive elaboration of the Modes of Coordination framework, Diani argues that in "*civil society, the field comprises all voluntary organizations engaged in the promotion of collective action and the production of collective goods*" (2015:12-13).

Figure II.1 Diani's Modes of Coordination of collective action (Source: Diani 2015:16)



As we have seen, from a relational perspective, a field can thus be interpreted as a network and analyzed in terms of the interactions between members of a field and the structures that emerge from patterns of interaction. From this, Diani concludes:

> *When analyzing civil society, we should focus on the structure of the cooperative ties that develop between voluntary organizations (as well as between them and other types of actors); we should try to identify the lines of segmentation within civic networks as well as the positions within them that secure their overall integration (if any); finally, we should explore the matches and mismatches between the characteristics of civil society actors and their network position* (2015:13).

To guide this analysis, Diani proposes the Modes of Coordination framework, that is focused on "*relational processes through which resources are allocated within a certain collectivity, decisions are taken, collective representations elaborated, and feelings of solidarity and mutual obligation forged*" (2015:13-14). The two mechanisms behind these processes are *resource allocation* and *boundary definition*, which thus resembles the distinction by Laumann and colleagues, who characterized "*two general types of interorganizational relationship, linkages based on resource transfers and those based on interpenetration of organizational boundaries*" (1978:463, also see Eggert 2014).

However, Diani emphasizes that both processes play out on various levels, as decisions on the allocation of time, money, and energy must be taken by each individual activist as well as by each organization. Resource allocation for the individual may thus include decisions on whether to get involved with a specific issue or abstain from it, whether to join a specific group or not, whether or not to attend a protest event, join a strike, participate in a meeting or not, whether to sign a petition or not get involved (Diani 2015). Similarly, these choices must also be made by organizations, which "*are regularly faced with dilemmas related to their issue priorities, to their choices of tactics, and to their alliance-building strategies*" (Diani 2018:4). Resource allocation on the organizational level can thus be defined as "*the set of procedures through which decisions are taken regarding the use of organizational resources*" (Diani 2015:15), meaning the choices collective actors make in terms of campaigns, action, participation, or collaboration. A relational perspective is naturally interested in the networks generated by these (interorganizational) interactions, which may vary substantially, as

> *in some cases, organizations may concentrate most of their resources on their own projects and devote a very limited amount of resources to collaborative initiatives, resulting in fairly sparse interorganizational networks. In other cases, resources invested in collaboration may be substantial and may lead to fairly dense networks* (Diani 2015:15).

To exemplify this, we can easily imagine a resource-rich and well-established organization with a certain level of influence to choose prioritizing an own campaign in their issue-area over the arduous struggle of forging coalitions and engaging in compromises. For less resource-rich groups with little influence it might make more sense to pool resources and negotiate common claims with other actors to gain more attention and leverage joint political power. In both cases, actors might just as well choose other tactics, depending on goals, opportunities, and circumstances – what I argue here, is that these choices create very different networks of interorganizational ties.

Analogous to *resource allocation*, the mechanisms associated with *boundary definition* form another dimension in the typology of Modes of Coordination of collective action. In line with a field perspective, Tilly defined social boundaries as "*any contiguous zone of contrasting density, rapid transition, or separation between internally connected clusters of population and/or activity*" (Tilly 2004:214). This means we may expect denser interactions among members within such a boundary, and fewer interactions across boundaries. Social boundaries can thus separate actors of a field into different communities or subcultures, each characterized by strong ties of internal solidarity. This resonates in Diani's definition of boundaries as *"criteria that classify elements of social life in different groups and categories, while shaping the relations between those elements both within and between those groups"* (2015:16). In other words, who belongs to a group, a phenomenon, or a movement, depends on whether this actor defines himself as being a part of it and is recognized by others as such. This may mean the individual solidarity one feels toward a group, or the way one feels part of a collective identity, and it may mean the way a group describes itself and its place in relation to other groups. The ascription of meaning to an action may draw upon the feeling of being part of a common struggle as well as drawing on past experience and historical trajectories. Naturally, these negotiations of identity involve exchange with others, and thus boundary definition and alteration both result from past interaction as well as shape future interaction. Boundary definition in interorganizational exchanges, as Diani (2015) studies them, may thus happen where Simmelian circles intersect, e.g. in the multiple membership of individuals in organizations. These bonds of potential interpersonal interactions can in turn lead to strong feelings of solidarity among organizations, and hence naturally draw clear boundaries towards other collective actors. Or, as Eggert put it: "*links between organizations through shared core members and personal ties can serve as a proxy for processes of boundary definition and collective identification*" (2014:372).

The operationalization of these two classes of mechanisms in relational terms allows for a typology of logics of collective action along the structures of networks that evolve in both dimensions, "*which is particularly useful for distinguishing among various types of organized collective participation […] in different contexts*" (ibid.). Hence, limited or intense boundary work as well as limited and intense resource exchanges may combine to a typology of four ideal-types of Modes of Coordination, as shown in Figure II.1 above. The empirical phenomena that resemble these ideal types can all be seen as instances of collective action yet may all follow different logics of interaction. However, the empirical reality might be much messier than these clear-cut Weberian ideal-types, and in every episode of contention, it is likely to identify a coexistence of the different analytical categories (Diani 2015). It is precisely this multiplicity, that allows for an attempt to classify distinct categories of collective action in different places or times, thus offering a promising alternative to the terminological confusion discussed in section II-i.

As I have argued earlier in this chapter, *social movements* are often seen as the generic category with which to describe any episode of collective action. In the framework of Modes of Coordination however, they are but one type of coordinating collective action, *"defined by the coupling of dense networks of informal interorganizational exchanges and processes of boundary definition that operate at the level of broad fields rather than specific groups/organizations"* (Diani 2018:7). Empirically speaking, we expect to find strong and dense networks both on the dimension of boundary definition (e.g. by a high overlap of members among many organizations in the field) and on the dimension of resource exchanges (e.g. by a high overlap of mobilization for campaigns, petitions, or protest events among many organizations in the field). Strong interactions in resource exchange are necessary, since "*in order to mobilize, movements need different types of resources, and engaging in resource exchange with others can provide organizations with resources they are lacking*" (Eggert 2014:373). At the same time, the social movement mode of coordination relies on strong ties of boundary definition, as "*these ties provide organizations with a collective identity that goes beyond single organizations and act as motivation for participation*" (ibid.).

However, engaging in these processes might not seem beneficial for every actor, as it (initially) involves informally negotiating joint tactics, common messages, problem definitions, policy demands, and target audiences – in other words: *"in a social movement MoC, transaction costs tend to be high"* (ibid.). The cultural and symbolic dimension of boundary definition is also strong in social movements, as a collective identity is important to *"secure the continuity of social movements over time and space"* (ibid.:8). We can thus easily imagine that the identification with a movement can serve as strong bonding capital, meaning the awareness of taking part in 'one struggle, one fight' even when geographically or temporally apart can be a strong motivational factor. Diani highlights the importance of recognition and perception in this regard, as one group is never part of a movement

> *unless its members as well as external observers recognize it and its actions as such, and unless both the organization and its members are connected to other actors and initiatives on the same ground. In this sense, individual multiple memberships can operate as an important signal of the perceived proximity and solidarity linking different independent organizations* (2018:8-9).

Without constituting a social movement, these boundary definitions may be strong in another mode of coordination, namely that of *subcultures/communities*. This is characterized by *"a process in which interorganizational linkages are sparse, yet there are widespread feelings of identification with a much broader collectivity than that represented by specific organizations, and a set of practices, multiple affiliations, and so forth that support it"* (Diani 2015:23-24). Thus, in this mode, people do feel strong bonds of solidarity, yet resource exchanges remain limited. This may happen both in the absence of strong organizational structures (e.g. in the case of authoritarian regimes suppressing these elements of civil society) and parallel to or apart from the existence of these structures. An example for this mode may be consumer boycotts in which individuals might strongly perceive themselves as part of a vegan, an organic, or other diet-related movement, yet carry out boycotting actions in a strictly individual way without the need for any groups to coordinate these actions (Diani 2018). For this study, it is important to note that Diani suggests digital communication to likely facilitate the emergence of this mode of coordination, and digitally mediated protest phenomena are likely to be best associated with this category of the typology, as

> *from the point of view of Modes of Coordination, phenomena such as Occupy or Indignados, or even the Arab revolts […] seem best conceived as instances of communitarian (in a broad version of community) types of collective action rather than fully fledged social movements* (2015:213).

The *coalitional* mode of coordination must not be confused with a broad understanding of coalitions, but instead carries distinctive traits in this framework that may at times look similar to the social movement mode, yet differ in their processes of boundary definition, as "*organizations may become involved in dense collaborative exchanges with groups that have similar concerns, yet without necessarily coming to share a broader identity or an extended time perspective" (Diani 2018:12).* We must imagine actors in this mode as willing to pool resources, e.g. for specific campaigns, to exchange know-how and information, to formulate similar policy demands, and to advocate for the same change, yet with limited investment in forging a longer lasting collective identity. For example, on a very local scale, we can imagine groups from different backgrounds, with different personnel, and different value-systems to promote collective action in a joint coalition when it comes to an issue that touches all group's agendas. We can imagine a campaign to ban cars from the city center to be supported by cycling activist groups, by health groups, climate change groups, by parent groups concerned with their kid's safety, etc. Each group may see this campaign as a logical issue within their respective broader field, and all of them may sign the same petition, stage joint protest events, print and disseminate the same information flyers, yet not necessarily build a long-lasting understanding of being part of the same collective and thus being involved in boundary work. Diani argues that

> *coalitions exhaust their function when their goal is achieved, or when it is clear that the cause is lost. There is no left over from a coalition in terms of feelings of belongingness to a broader collective entity, or of attempts to build a longer-term and more solid collective identity by linking the specific campaign to larger collective projects, encompassing multiple actors* (2015:22).

The fact that coalitions may very well *"evolve gradually into fully-fledged movements" (ibid.:23)* serves to illustrate both the possible interplay of different Modes of Coordination and the analytic distinctions that allow to distinguish between long-term and wider reaching movements and short-term and likely single-issue focused coalitions.

The last mode of coordination to be discussed is the *organizational* one, in which interorganizational networks are sparse, both on the dimension of resource exchange and on the dimension of boundary work. Interactions remain limited to the relationship between individual and organization, meaning that we may imagine a group asking its members to sign petitions or boycott products, thus engaging in action, but with little necessity to invoke exchanges with other groups (Diani 2015,2018). In this mode, organizations *"may operate primarily on their own terms without necessarily developing particularly strong identity bonds to other groups or without engaging in systematic negotiations with other actors on matters of strategies or tactics" (Diani 2018:14)*. This may, for example, be the case where groups shy away from the transaction-costs of engaging in negotiations about joint tactics or common goals and possess the necessary resources to operate on their own. In other cases, available resources might play a limited role and the reason not to seek involvement with other groups is plain competition for resources, where an organization favors *"strengthening the peculiarity of their profile […] or securing a specific niche by becoming quasimonopolist owners of a specific set of issues" (Diani 2015:18)* over the danger of watering-down their own priorities in the process of negotiating compromises. Diani argues that this mode may apply to a broad range of phenomena and with varying degrees of involvement of individuals in organizations, from loose checkbook memberships with limited internal identity building to sects or radical political groups with strong internal identity building (ibid.).

While a single episode of collective action might be comprised of different modes operating independently or highly entwined, the important contribution of this framework in the study of collective action is that it provides a typology of ideal types based on a truly relational perspective that allows us to describe phenomena as distinct in their structural patterns rather than subsuming them under a generic header. For a study on collective action phenomena that are deeply rooted in digitally mediated forms of communication, this framework can help bridging the opposition between an optimistic technological determinism and a mere dismissal of digitally mediated action as random noise. In other words, describing interactions of individuals and groups in terms of Modes of Coordination will allow us to shed a light on the actual patterns that do or do not emerge in a digitally mediated setting and not only study which modes emerge among different (sets of) actors, but also what types of actors might be more likely found to coordinate in one mode or another. We must however keep in mind, that this framework was empirically applied by Diani (2015) in a study based on older interviews with individual activists and thus at a time when SNS might have had a limited role or not even existed. Therefore, this study is - to the best of my knowledge - the first application of this framework to a digitally mediated setting and is as such also an exploration of the applicability of a theoretical framework that, as Diani argues *"enable[s] us to capture the variety of relational patterns taken by collective action, **regardless of its media**" Diani 2015:11, emphasis added).* For this application, it is vital to highlight that I will follow an understanding of groups that is rooted in the concept of partial organization, as discussed in this chapter. Thus, I will understand the field of anti-asylum-shelter groups on Facebook as one comprised of the partial organizations of public Facebook pages. We thus understand them as distinct entities with some organizational traits, like a locality and a set of members, however informal their membership may be. The following chapters will link these theoretical assumptions with empirical data and discuss the operationalizations of the two mechanisms of boundary work and resource exchange.

II-vi Of Positions and Ties: Framework Adaptations

Before we introduce our case in more detail and discuss the specific questions, sets of data, and methodological tools of our analyses, let us linger with conceptual considerations for a little while longer. It is important to state here that this study will depart both conceptually and empirically from Diani's own approach to Modes of Coordination. This means, we will study MoC as properties of networks rather than of organizations and hence base our operationalization solely on *network ties instead of actor positions*. This focusses less on the similarity of actors that coordinate in one mode or another, but rather on the networks that result from the processes associated with resource exchange and boundary definition. Whereas Diani's own application follows an empirical approach based on the detection of equivalent actors and thus sees Modes of Coordination in light of a positional approach, I follow a reading of the framework that focusses more on the multiplexity of ties and hence the way the same actors may be entwined in different networks at the same time. While these different readings will become more manifest in the empirical part of this dissertation, it is necessary to state here that this is by no means a critique of the initial approach, but rather the deliberate choice to focus on a different aspect of the framework and hence offer a complementary operationalization of it.

In general, Modes of Coordination of collective action offer us a typology to disentangle collective action phenomena otherwise conflated by opaque metaphors of "networks" or "movements". This entails breaking down our observations into subgroups, either of actors that chose to coordinate in one mode or another, or into ties that can serve as ideal type representations of these modes. Hence, we basically face what Borgatti and colleagues called a "positional" or "relational" distinction, where the former is concerned with identifying "*classes of nodes that have similar structural properties*" and the latter "*seek[s] clusters of nodes that are connected to each other*" (2013). In this distinction, positions are often understood in terms of their structural or regular equivalence, (Breiger, Boorman, and Arabie 1975; Lorrain and White 1971; White and Reitz 1983), meaning that actors occupy similar positions if they hold equally or similarly structured ties to others. The idea of identifying equivalent positions is based in the notion of roles (Nadel 1957) as specific constellations of relationships, and hence as inherently relational (Diaz-Bone 2019). Brandes sums up a general understanding of position in networks:

> *a position characterizes what the network looks like from the point of view of an actor, and multiple actors sharing traits and perceiving comparable*

environments are considered to be subject to similar opportunities and constraints, resulting in similar actions and the assumption of similar roles (2016:1–2).

A classic example of this would be a school, where different teachers each have a "teaching" relation to the same class of students and hence occupy a similar position. A look at these configurations of teaching-ties would clearly group all teachers as an equivalent subgroup of actors: their similarity is based on having equivalent ties to others, instead of forming a cohesive subgroup that is internally tied. Analyses following the positional approach typically try to identify these equivalent sets (or "blocks") of actors, for example through algorithms like CONCOR (Breiger et al. 1975) and then looking at distributions of ties between and across these blocks. However, critics have questioned the explanatory power of a partition of nodes into different blocks, mostly for the arbitrariness of the number of partitions and the fact that actors within the same block do not necessarily need to be connected (Saunders 2007, 2015). Thus, a relational approach that studies the actual relationships (i.e. ties) might provide a valuable alternative. For example, if we postulate that boundary-defining processes are relevant for the formation of collective identities and lasting bonds of trust that eventually allow actors to engage in high-risk contentious action together, it might make sense to study the actual collaborative ties that represent said processes. For Saunders, the distinction between positional and relational approaches does certainly imply different methodological choices in the analyses of networks, but she goes deeper than that, by phrasing the question of social relations and social structures as a hen-and-egg problem:

> *Positional (sometimes called 'structural') approaches to network analysis assume that it is the pattern of relations that results in given behaviours and beliefs, whereas relational approaches allow us to view the pattern of relations as a result of behaviours and beliefs rather than a cause of them* (2007:231).

Ultimately, these questions will remain open to debate, and divisions between these approaches are not clear-cut. While Diani choses to study equivalence blocks, he nonetheless also studies the distribution of ties both between and within blocks[11]. And while my own approach choses to focus on the study of ties of both resource exchange and boundary definition, we nonetheless apply node-level positional measures like centrality. Thus, in my own reading, positional and relational approaches are not so much competing but rather complementary approaches to study collective action phenomena as networks. When I will examine different types of ties among organizations and read each one as a form of resource exchange or boundary definition, I will conceptualize the distinction between "intense" or "limited" exchange of the original MoC framework (see Figure II.1) as the co-presence of multiple resource exchange ties or the relative weight of boundary exchanging ties. Empirically speaking, Modes of Coordination thus become networks that result from different combinations of ties. I believe this to be very well in line with the original formulation of the framework, yet provide an innovative reading that simply focusses on different aspects, namely the multiplexity of ties and the co-existence of different modes in the same episode of contention, that are better understood by a tie-centered than a position-centered approach. I want to clarify this with two arguments:

[11] I do not want to go deeper into the differing operationalization-choices that come with a different reading of the framework at this point. Chapter IV-iii will pick this debate up and discuss it in more depth.

First, this study adapts the framework to a digital setting, where the notion and meaning of different ties is less established and not well understood. While collective action research based on surveys has a long-standing tradition and an understanding of what concept should be "measured" by each question, the study of collective action by means of digital behavioral data is yet in its infancy. Often, studies have relied on hyperlinks as "signs of belonging" (Vicari 2014), as expressions of feelings of similarity (Tateo 2005), or as tools to spread ideology and foster mobilization (Caiani and Parenti 2013). I believe that an adaptation of the framework to the digital setting that puts ties into its center can help us disentangle the various ways actors are interconnected and move discussion toward a more nuanced reading of the various ways, ICT is used in collective action. This is also reflected in the overarching research question of this dissertation, which seeks to contribute to an understanding of the role of ICT for contentious collective action. I believe this purpose is best served by a rigorous focus on the ties and networks that emerge from actors' usage of SNS, before we come to an understanding of roles and positions. Thus, by focusing on ties, their strengths, and their combinations, we can start bridging the divide between digital research and collective action theory outlined in this chapter.

Secondly, Diani concludes in his own application that "*variable combinations of such mechanisms* [i.e. resource exchange and boundary definition, MH] *define different structural positions within fields, reflecting different logics of network multiplexity*" (2015:201). While clearly, positional approaches have their upside in the conceptualization of social roles, as we have discussed above, the division of actors into discrete positions does have a severe downside when multiplexity is concerned. By confining actors to one and only one position, we do acknowledge that multiplex ties of boundary definition and resource exchange are in place, but we do not allow a multiplexity of Modes of Coordination themselves. However, as Diani observes in his next concluding point, "*each episode of collective action combines different modes of coordination*" (ibid.). When we think of this point consequentially, there is no reason why the same actor might not be involved in different modes at the same time – although with different alters. Conceptualizing MoC as types of ties allows us to precisely capture that behavior – one actor may be involved in ties representing a social movement mode with one set of alters, and in the arguably less intense ties of the organizational mode with a different set of actors. In addition, thinking of MoC in terms of specific combinations of ties lets us understand their logic better by looking at the different networks that emerge from these ties. For example, we might expect an organizational type of tie to produce larger, yet looser networks, while a social movement type of tie may produce networks that are smaller, yet denser (Baldassarri and Diani 2007) However, as mentioned above, this shift in focus comes with serious limitations as well, that become most evident in our understanding of the *organizational* mode of coordination. For Diani, this mode is able to (also) represent a behavior where resources are largely devoted to an organization's own activities, thus contributing to a cause without explicit collaboration with others. This behavior likely leads to organizations being in an isolated position in an exchange network, which in turn makes it easy to group such an organization in the *organizational* mode. In a tie-based understanding we are not able to capture this phenomenon, but require at least some degree of networking activity, namely weak ties of resource exchange and weak ties of boundary definition to speak of an organizational mode as a network.

This is an evident limitation of this understanding, illustrating my point that a tie-based approach is complementary to a positional approach rather than meant to replace it.

In conclusion, moving the focus away from positions and toward ties is not only an operational choice, but also has a conceptual underpinning that stems from its innovative application to a different type of data as well as from some shortcomings of the positional reading of this framework. Therefore, this dissertation can not only generate new substantial knowledge on its case, but at the same time enrich existing theoretical debate with an innovative perspective. Furthermore, an application of this framework to a *digitally mediated* collective action phenomenon is original in its contribution to the conceptual debate, as it will seek to test the exploratory power of a relatively novel framework in the collective action debate.

To sum up, this chapter has attempted to set the theoretical stage on which we will examine our specific case. I have argued the need for such research in light of an under-explored and at times controversial understanding of digital communication technology and collective action. To do so, a perspective rooted in a relational understanding of collective action that focuses on how organizations interact and what ties and structures emerge from these interactions, has been established. From this vantage point, we can formulate an overarching questing guiding the following analyses: *What is the role of Information and Communication Technology for contentious grassroots organizations?* While a comprehensive and definitive answer is unlikely to be found by any single scientific project, let alone a dissertation, we can nonetheless contribute insights and findings derived from four sets of more nuanced and more operationalizable questions that will be spelled out in the following chapter. These will be applied to the digital communication data I was able to gather on the case of Anti-Asylum-Shelter protest groups in Germany. The choice of this case is neither drawn from the interest in a systematic comparison of left-vs-right groups nor in a comparison of countries[12], but from a substantive interest in the case and its societal and political salience in these troubled times. Indeed, our theoretical reasoning was explicitly rooted in scholarship on collective action, digital communication, and organization, confining the debate on specificities of the extreme right to the case selection in the following chapter.

Empirically, this study will focus on an in-depth exploration of the activities, the debates, and the networks that can be identified among the organizations of our subfield. To best understand our case, in a Weberian sense, we will thus seek to map the relevant actors and describe patterns of both spatial and temporal activity, to understand the *who* and the *what,* before engaging a deeper understanding of the debates, topics and frames that are produced through these actors' interactions. Ultimately, if we want to understand the role of ICT for these actors from a relational perspective, as I have stated above, we have to move toward an understanding of the meaning of different types of patterned interactions and the structures they produce. Like this, we "*employ networks beyond the metaphor*" (Pavan 2015:915) to understand that "*the content of ties determines the type of relational structure actors engage in*" (ibid) and that "*actors do not engage in all relations in the same way*" (ibid). Doing so through the lens of *resource exchange* and *boundary definition* and the Modes of Coordination that emerge from the combination of these two is thus "*more than a*

[12] Both comparisons are highly relevant and have drawn significant attention. For example Bennett, Segerberg, and Knüpfer (2018) have studied the interplay of left-right ideology, organizational preferences and new communication technology, while Caiani and Parenti (2013) and Pavan and Caiani (2017) have systematically analyzed right-wing online networks across Western democracies.

network exercise" (ibid), but can help us "*understand the potentialities and constraints to action that come with a specific relational pattern*" (ibid).

Before we get there, however, the following chapter will illustrate in detail how this exploration will be structured, which sets of more detailed questions can guide the empirical analyses, and what combinations of data and methods will be used, along with providing a deeper understanding of our case and of its position within the German political right-wing.

Chapter III - Research Design

After having laid out the principal question guiding this thesis and the theoretical lens that will be used, it is time to address what exactly this lens will focus on. Especially since this dissertation does not apply a comparative design but rather opts for an innovative combination of theory and data in an in-depth analysis of a single case, it is crucial to elaborate on the salience of this case. That being said, the objects of study in this thesis can be very generally described as *German anti-asylum-shelter (AAS) groups on Facebook*. As argued in the introductory chapter, my interest in this area is grounded in two observations: On the one hand, a resurgence of the political right in Germany and on the other hand, the ubiquity of digitally mediated communication in collective action episodes. While the latter observation and especially the challenges that arise from it in terms of conceptualizing collective action from a theoretical perspective have been discussed in chapter II, it is the former observation that needs some elaboration at this point.

Therefore, this chapter will begin with an overview of relevant party and non-party actors on the far right in post-war Germany. Through that, we will see how the current decade has brought about a resurgence of right-wing activity, involving both new and old actors and being related especially to the opposition of migration. Against this background, we will illustrate how a recent wave of scholarly activity has treated this phenomenon and how we can position this dissertation within it. Once we have done so, we can move on to illustrate the criteria of selection both for the organizations and for the platform that actually make up our case. This way, by the end of the first section of this chapter, we will have a clearly defined population of AAS-groups that we are about to study. After that, the second section of this chapter will clearly state how we will study our case, by introducing the sets of research questions, which result from both our selected case and the theoretical perspective we take toward it. Lastly, the third section of this chapter will lay out our toolkit to answer these questions, both in terms of the data that were collected and in terms of the methods that were applied.

III-i Case: German Anti-Asylum-Shelter Groups on Facebook

Perhaps the most striking example of a renaissance of the right is its electoral success. For a long time in post-war Germany, parliamentary representation of the right wing (i.e. very broadly: parties positioned to the right of the Christian Democratic/Social Union, CDU/CSU) was limited. Founded in 1964, the National Democratic Party (NPD) has been and continues to be the strongest party of the extreme right, albeit with limited success. Not once in its history has the party been able to surpass the 5 per cent-hurdle to enter the German national parliament, the Bundestag. During the 1990s and the 21st century however, the party was able to win seats in elections in municipalities, in some of the (East-)German Länder, as well as in European elections (Lepszy 2013). The "Deutschlandpakt" with the Democratic Union of the People (DVU) and the German Party (DP) between 2005 and 2009 was an attempt to unite the extreme right, that resulted in a vote share of 7.3 per cent in the regional elections (Landtagswahlen) in Mecklenburg-Western-Pomerania in 2006 (Braun, Geisler, and Gerster 2009). As of 2018 however, the party is no longer represented in any German Landtag and in 2019 it lost its single seat in the European Parliament. This limited success of the NPD goes hand in hand with a fragmentation of the extreme right political spectrum in recent years, that saw both the founding of new parties like the Right (Die Rechte) and the Third Way (Der III. Weg) in 2012 and 2013, as well as participation in elections by local initiatives of the anti-Islam so-called "Pro-movement" (Anon 2017). While these parties and especially the NPD have established political structures and organizational resources, such as establishing contacts to militant Neo-Nazis and "Kameradschaften" (comradeships), organizing local and international festivals, mobilizing street protest, or owning and leasing property, their political representation has been limited in recent years (Braun et al. 2009).

Thus, the parliamentary renaissance is driven by a new actor, the Alternative for Germany (AfD). Founded as a party in 2013 with a euroskeptical and anti-Euro (the currency) agenda, the AfD changed its leadership multiple times, leading to two major splits and a gradual shift toward the more radical right. Within a five-year period, the party has gained representation in all German Landtage, in the Bundestag, and in the European Parliament, promoting an anti-immigration and anti-establishment agenda. In September of 2019, the AfD was able to celebrate its biggest electoral successes yet, reaching 23.5 per cent of the vote share in the Land Brandenburg and even 27.5 per cent in the Land Saxony, where the ruling Christian Democrats were at first hesitant to denounce a possible coalition government with the AfD. Especially in the rural Eastern parts of both Brandenburg and Saxony, the AfD even emerged as the strongest party in many constituencies.

Without delving too deep into the terminology of radicalism, extremism, or populism, I believe one of the best fitting definitions for the AfD is given by Rydgren, who characterizes an Extreme Right Populist (ERP) party by its *"fundamental core of ethnonationalist xenophobia (based on the so-called 'ethnopluralist doctrine') and anti-political establishment populism" (2005:433).* A report by the German domestic intelligence service, Bundesamt für Verfassungsschutz (BfV) analyzed the activity of the AfD, its youth organization Junge Alternative (JA), and individual politicians both offline and on Facebook, finding that *“some leading officials advance an understanding of the people [‘Volk’] that is strongly ethno-centered and incompatible with the guarantee of human dignity. Other officials or members issue a strict ethno-nationalist mindset”* (Bundesamt für Verfassungsschutz 2019, translation MH[13]). The report generally questions the AfD’s stance on the free democratic basic order (“freiheitich-demokratische Grundordnung”) and suggest a monitoring (“Prüffall”) of the party as a whole, and a deeper intelligence observation (“Verdachtsfall”) of the JA and the party’s branch “Der Flügel”. While there is ample debate about the populist, radical, and/or extreme nature of parties on the right (Fawzi, Obermaier, and Reinemann 2017; Minkenberg 2018; Mudde 2004, 2016), this debate is not one that needs to be discussed in more depth for this study. It suffices to diagnose that a new party has emerged in the German political spectrum that offers representation with an agenda based on issues the far/populist/extreme right is deeply concerned with: ethnonationalism, opposition to immigration and to the establishment.

While right-wing parties may be the most formally organized actors in this spectrum, the observation of a resurgence of the right stretches beyond the realm of parties. A famous example of right-wing mobilization can be found in the case of the Patriotic Europeans against the Islamization of the Occident (PEGIDA). PEGIDA started on Facebook as a group that soon turned to a public page in October 2014, and was able to mobilize up to 25,000 people for street protests in Saxony’s capital Dresden (called “Montagsspaziergänge” in reference to the civil protests during the

13 Original quote: “Zunächst vertreten einige Führungsfunktionäre ein mit der Menschenwürdegarantie unvereinbares, stark ethnisch konnotiertes Volksverständnis; andere Funktionäre bzw. Mitglieder äußern teils eine streng völkisch-nationalistische Grundhaltung.” If not marked otherwise, all translations from German to English are made by me.

collapse of the GDR, which were held every Monday) and branching out to cities all over Germany (Stier et al. 2017; Vorländer, Herold, and Schäller 2016). Despite going "offline" with protest rallies, Facebook remained PEGIDA's main platform to voice their issues, as the protesters largely refused to speak to the media (referred to as the "Lügenpresse" [lying press]) and/or researchers (Stier et al. 2017). Early observers questioned the political position of PEGIDA, who claimed to represent the concerned citizens in the center of society, yet expressed positions that, as discussed above, characterize the (extreme) right. The controversial professor Werner Patzelt[14] (2016) argued that while protests have radicalized, showing an increasing rejection of the German state and of refugees and asylum-seekers, protesters themselves do not represent the classical extreme right-milieu in Germany. A study by Walter (2015) has found a strong affinity of PEGIDA protesters to the new right-wing party AfD, while Daphi et al. (2015) identified overt hate speech and racism at anti-immigration demonstrations. For the sake of this study, it is important to situate PEGIDA as one example in which digitally mediated communication played a pivotal role in the coordination of collective action on the political right, largely in the absence of pre-existing (formal) organizations. Thus, it serves to illustrate both the importance of SNS in the study of collective action, as well as the emergence of right-wing protest in Germany.

To further elaborate on the setting and the zeitgeist, in which we must situate the case of AAS-groups, we can also cite examples of anti-immigration protest in which already existing loose organizational networks were used to mobilize for contentious

[14] Whose proximity to the AfD has been an issue of debate (Meisner 2019).

collective action. The network Hooligans Against Salafism (HoGeSa) was able to stage some of the biggest anti-immigration/anti-Islam demonstrations, with a peak of up to 5,000 protesters in Cologne in 2014. While Facebook was used as a tool to communicate internally and externally, we can reasonably assume that the existing structures of hooligan groups and their experience in violent conflict with the police, along with interpersonal affiliations to comradeships and right-wing parties allowed them to forge at least a short-term coalition based on violent confrontation (Anon 2014; Ruf 2016).

This is by no means an exhaustive account of the political right in Germany and does not aim to be one. Instead, these examples show that within the broad field of the political right, a wide range of actors have emerged or continue to be active, with very different organizational structures and logics, different tactics and strategies, and different usage of ICT and SNS. Thus it becomes clear, as argued in chapter II, that speaking of the right-wing as a social movement (Castelli Gattinara and Pirro 2019) may blur very distinct traits of specific phenomena that differ in the way they coordinate and interact. Also, as it is beyond the scope or feasibility of a dissertation to study the entirety of the German political right in the wake of what soon became the so-called “refugee-crisis”, I strategically opt for an approach that allows for an in-depth mapping of the subfield of AAS-groups from a Modes of Coordination perspective. While I argue that they are part of the political right, they do form a distinct subfield, with groups forming not around a general anti-immigration stance, but specifically and explicitly in opposition to the erection of asylum-shelters. As we will see in the analyses, these groups do engage in (mutual) acts of recognition significantly more amongst themselves than with other organizations, and many groups follow similar naming-patterns for their Facebook pages or visual-patterns for the choice of their logos. It is also important to note that protest against asylum-shelters was almost nonexistent in the years before 2013. The phenomenon under investigation here is thus one that that we could witness in its birth, its prime, and its eventual (relative) decline, as the analysis will show. In fact, the opposition to asylum-shelters has become a distinct topic even in the German federal criminal records of the Bundeskriminalamt (Anon 2018), being recognized as a distinct sub-set of right-wing political activity.

However, I find myself among the observers who might be accused of jumping to conclusions about the political nature and standpoints of members of AAS-groups. After all, opposition to migration must not necessarily be a feature exclusive to the right, as it must not automatically feed from a racist, ethno-nationalist, xenophobic mindset. In fact, survey data from 2015 showed that a majority of Germans were skeptical of the integration of refugees, and articulated fears related to competition on the housing market, the labor market, or a growing influence of Islam as prime concerns (Infratest Dimap 2015). These issues are typical, but not exclusive topics of the political right. In addition, a four-wave survey of PEGIDA-supporters (Patzelt 2016) found that a majority of street-protesters were both opposed to immigration and right-wing-radicalism, politically positioning themselves in the center of a left-right-scale.

Figure III.1 Street protest against asylum shelters

(Source : Schulze and Frykman 2015 Image by: Christoph Schulze)

This seemed to be the case also among the AAS street protesters, that frequently showed signs like the one in Figure III.1, saying “We are no Nazis” or “We are no Nazis, but local residents”. This however contradicts observation by left-wing monitoring groups that some AAS-groups were deeply involved with the right-wing NPD (Dittrich 2015). Thus, even though I stand by the earlier assumption of grouping AAS-groups as part of the political right, the case deserves the scientific benefit of the doubt. Therefore, it becomes vital from a Weberian understanding of sociology as “verstehend” to explore the actual content that is produced in AAS-groups and circulated in their networks to get a better substantial understanding of the phenomenon and to come to scientifically sound conclusions about the political nature of these groups.

When I began working on this project in 2016, I was apparently not the only scholar observant of a novel dynamic between digital communication and the political right. Therefore, the following paragraphs will briefly illustrate the (mostly recent) scholarship on this topic, to show that we can position this dissertation within an ongoing and highly relevant scientific debate. This account is by no means exhaustive and its aim is not to introduce and discuss a comprehensive theoretical argumentation, but rather show what empirical studies might be relevant to our undertaking. This way, we can clearly show that our case is a relevant one that draws scholarly attention, while at the same time we can also show how this study can aim to fill a still existing research gap.

My choice to I opt for an exploratory approach reflects the fact that much scholarly work in the study of ICT or SNS and collective action has addressed the political left, leaving "uncivil" (Ekman 2018) engagement of the extreme right – not only, but especially in reference to digital coordination – a still understudied phenomenon so far (Caiani 2017; Eggert and Giugni 2015). In addition, in the field of both immigration and anti-immigration movements, empirical literature is still rare, as Eggert and Giugni note: *"Much more work is required in order to better understand under which conditions social movements by, for, and against migrants mobilize and through which processes and mechanisms"* (2015:168). Similarly, Pavan and Caiani have diagnosed that "*the use of digital media by ER [Extreme Right] groups has been partially neglected, when not underestimated*" (2017:170).

However, a small but growing number of studies has addressed the issue, although from different perspectives and with different foci. Early empirical contributions on right-wing movements and the internet include Burris, Smith, and Strahm, who have adopted a network approach by analyzing the hyperlinks between American white supremacist groups' websites, arguing that links are *"ties of affinity, communication, or potential coordination"* (2000:215). They found a decentralized structure in which stronger ties exist between groups who focus on cultural identity than between competitive groups such as parties or enterprises. Tateo (2005) replicated this approach to study the Italian extreme right, finding a coherent yet loose network structure in which revisionist, nostalgic, veterans, and cultural groups are the central actors. Other case studies, like Zuev (2013) explored ultranationalist Russian websites from a social movement perspective to identify structural properties, ideology, and central actors. In another study, Froio (2018) focused on a network of French far right groups and the question how Islam is framed among different groups.

In a comparative study across six different countries, Caiani and Parenti (2013) analyzed right-wing networks in light of political, cultural, and technological opportunity structures. In the German case, which is of interest for this dissertation, they identified a cohesive network with right wing parties as the central actors. Based on this study, Pavan and Caiani (2017) analyzed hyperlink networks in six European countries, including Germany, explicitly linking the study of anti-European frames with that of network structures and centrality. In this study, they explicitly treat "*Web links between organizations as potential means of coordination*" (2017:172) and find that in the German structures, "*political movements, subcultural organizations (…) and the NPD*" occupy central positions. These result reiterates the need to look more into the role of formal organizations, such as parties, even when studying digitally mediated grassroots networks. Froio and Ganesh strengthen this aspect by noting that "*research on transnationalisation of the far right kept parties and movements separate probably because of the difficulty to find data allowing to account for both simultaneously*" (2018:518). They argue that research should focus on the interplay between grassroots organizations and what they call "*more established radical right organizations*" (ibid). This resonates well with the categorization of ideal types of different logics of action defined by Bennett and Segerberg (2013), in which one of the distinction between these types is the role that formal, established organizations (like right-wing parties in our case) play. Thus, even though SNS can "*ease cooperation between like-minded groups that do not enjoy similar opportunities in other parts of the public sphere*" (Froio and Ganesh 2018), we must not naively discard the role of established organizations in digitally mediated collective action, but rather critically address their influence. In line with this, Rucht (2018) highlighted the organizational hybridity of the German protest against refugees and asylum-seekers, that included both very formal (like parties) and very informal groups. In the case of Austrian AAS protests, Haselbacher and Rosenberger diagnosed a "*close interaction between institutional actors and protest networks*", studying "*the extent to which institutional actors are involved in the organization of protest events*" (2018:248).[15] This means that when investigating our case, we must not forget about the role of formal organizations of the political right, which has so far been largely left out.

More and more studies on the far right and digital media have moved from using websites for data to looking into SNS and other 'web 2.0' platforms as a source of data. Studying the dissemination of content among right-wing groups, O'Callaghan et al. (2013, 2015) have shifted attention to the use of Twitter or YouTube, finding users to be trapped in the ideological bubble of a platform's recommendation system. Klein and Muis (2018) compared both networks and discourses across right-wing Facebook environments in four European countries. Interestingly, they find that AAS-groups make up about a quarter of the right-wing groups they identified in the German case.

15 Both Rucht (2018) and Haselbacher and Rosenberger (2018) do however not employ a network perspective but rather use protest events and the framing thereof for their analyses.

In addition, we can identify a growing interest in the issue of anti-refugee/anti-asylum-seekers mobilization in recent years, yet not necessarily from a network or digital media perspective. While Della Porta's edited volume (2018) comprehensively studies solidarity mobilizations, only Castelli Gattinara's contribution (2018) explicitly focused on anti-refugee protests in Italy and France. It does, however, take a very different approach than this thesis, starting from the assumption of a "*broad, European, anti-immigration movement*" (Castelli Gattinara 2018:272; see also Castelli Gattinara and Pirro 2018) and using interviews to understand both motivations and repertoire choices of street activists. Violence against refugees and the predictive power of threatening events in Germany has been discussed by Jäckle and König (2018), while Ekman (2018) studied anti-refugee mobilization by the group "Soldiers of Odin" on Facebook. Schelter and Kunegis presented a conference-contribution that explicitly focused on AAS-groups on Facebook, finding that the *"German anti-refugee movement is inherently decentralized"* (2017). While they do review both online and offline protest data, temporal and geographical patterns, and the proximity to right-wing parties as important factors for organization and mobilization, their study does not analyze AAS-groups in terms of networked interactions and does not present a theoretical framework guiding the analysis. As the quotation shows, the study is further characterized by the movement-fallacy, that was discussed in chapter II of this thesis, automatically equating any joint action on a specific issue with a (social) movement. Therefore, while the study presents important insights and helps to delineate the object of study of my own research more sharply, the field is still missing a theory-guided comprehensive study of AAS-groups' usage of SNS to help foster our insights about the role of digitally mediated communication in right-wing contentious collective action.

In addition to an oversimplified or rather metaphorical use of the category of *movement* in many of the relevant studies, the same can often be said for *networks*. I believe that the role of networks needs to be discussed with greater care and not automatically be equated with the usage of SNS. González-Bailón and Wang criticize that *"the language of networks has become common currency in the different attempts to understand social movements in the digital age"* (2016: 97), but most studies fail to deliver empirical proof of the alleged flat hierarchies and fluidity of communication networks. They argue that *"claiming to live in the age of networks offers little information if we do not also provide a richer picture of what those networks look like and how they allow individual actors to communicate and organize"* (ibid.). Pavan also urges us to take networks seriously, arguing that "*whenever we equate networks that* ***necessarily emerge*** *from the use of digital media with a 'social movement' not only we are guilty of naivité but, more importantly, we are not adopting a relational perspective*" (2015:915, emphasis in the original). In other words, as networks are generated by *default* through the use of SNS, a truly relational perspective needs to carefully assess what different ties are generated through digital communication tools, what structures emerge from these ties, what content is (re-)produced through these ties, and which actors play a (central) role in these processes.

When we try to sum up what this brief review of literature tells us, we can conclude that there is a growing interest in the matter, but no study has - to my knowledge - addressed the issue of AAS-protest and SNS from an explicitly *relational* *perspective on collective action*. This, however, is precisely the research gap that my thesis attempts to fill.

As the case presented here is one of digitally mediated contentious collective action, the data is naturally digital, too. The choice of studying AAS-groups with data from the Facebook-platform is motivated by empirical considerations, as Facebook was simply "where it happened". While many studies in the field of social media and collective action used Twitter as a source of data (Kharroub and Bas 2016; LeFebvre and Armstrong 2018; Pavan 2013; Segerberg and Bennett 2011; Vasi and Suh 2016), it must be noted that the logic of Twitter is organized around debates rather than (more or less) stable groups. Also, studies have argued that the typical demographics of Twitter tend to be younger than Facebook's (Barberá and Rivero 2015; Mellon and Prosser 2017), which contrasts the findings of preferably older males engaging in recent German right-wing protests like PEDIGA (Patzelt 2016). In addition, Facebook groups are likely to reach a broader audience, as Twitter is by far less common in Germany (Frees and Koch 2015). Also, other examples of digitally mediated right wing phenomena like PEGIDA have shown the importance of Facebook over Twitter, making *"Facebook a more attractive medium for populist online communication"* (Stier et al. 2017:3). In other cases, such as the German right wing terrorist organization "Old School Society", Facebook was identified as the key medium for the mobilization of anti-refugee violence (Wyssuwa 2016). It is thus unsurprising that keyword searches on various combinations of the German terms for "refugee[s]", "asylum seeker[s]" and slogans directed against them on Twitter showed much less activity than on Facebook. Also, accounts by journalists (Geyer, Decker, and Honningfort 2015), watchdog NGOs (Berger and Hansen 2015; Dittrich 2015), and scientists (Müller and Schwarz 2018; Schelter and Kunegis 2017) hint at the salience of Facebook for anti-asylum protests. For these reasons, I opted to restrict my selection of organizations to the Facebook platform. An additional restriction is applied by the choice to select only AAS-groups with a public Facebook page and exclude those with open or closed groups. We must keep this limitation in mind, as some studies have indicated that (secret) Facebook groups are used differently by activists than more public channels (Hensby 2017). Facebook groups might thus be seen as representing a "*digital backstage*" (Treré 2015), where internal struggles and associated processes of identity formation and boundary drawing are more likely to happen than under scrutiny of the public eye. On the other hand, I believe it is ethically crucial to respect privacy settings of groups and restrict our observation to public pages that are "*visible to everyone on the internet by default*" (Facebook 2010). In addition, when I searched for AAS-groups, I found that the overwhelming majority chose to set up a public page instead of a closed group. Also, the content analysis in chapter IV-ii will be able to show that there was little fear of publicity in terms of expressing radical (and sometimes criminal) sentiments and the said processes of identity formation likely happened on public pages. Furthermore, our observation window stretches from 2012 to 2017 and thus for a span of time during which the Facebook corporation did very little to monitor or restrict problematic content or hate-speech. Thus, I find it reasonable to assume that most AAS-groups chose the visibility of public pages over the privacy of closed groups. Therefore, we are likely to capture the bulk of activities, even though we restrict our population to AAS-groups with public pages.

However, even when doing to, the challenge that remains is to formulate reproducible and transparent criteria for the selection of organizations that belong to the population of our subfield of German AAS-groups on Facebook. Therefore, I defined three criteria:

Firstly, groups are specifically against asylum- or refugee-shelters, not only against asylum-seekers, or refugees themselves, or against German migration policies.

Secondly, a clear geographic reference within Germany is made. This can be on national (i.e. "Deutschland"), state (e.g. "Bayern"), regional (e.g. "Sächsische Schweiz", "Oberlausitz"), or local level (e.g. "Löbstädt", "Berlin-Marzahn"), but excludes German-language groups with reference to a Swiss or Austrian locality.

Thirdly, the group has a public Facebook page, as Facebook pages are the empirical unit of analysis. As we have discussed above, it is important to distinguish Facebook pages from Facebook groups. Throughout this thesis, I will use the term group to refer to public Facebook pages of groups, not to actual groups in technical Facebook parlance. While pages and all content on these pages is public, groups often require membership and have more complex arrangement for the visibility of posted content. For both legal and ethical reasons, I excluded groups when they were non-public.

To obtain a most complete list of groups that match the abovementioned criteria, I followed a three-fold strategy:

Firstly, existing accounts of AAS protests have already assembled lists of Facebook groups that could be used as a starting point (Berger and Hansen 2015; Schelter and Kunegis 2017). While Berger and Hansen (2015) identified AAS groups in the East-German state Brandenburg, Schelter and Kunegis studied "*anti-refugee housing movements […] via dedicated Facebook pages*" (2017:2) Germany-wide. Both reports conclude that many groups follow similar naming-patterns, that include calls to "say no" or "resist" to a shelter already in the group's name. The groups identified by these studies could be used to generate a comprehensive set of keywords that can serve as markers of AAS-groups.

Secondly, these keywords were used both in the internal Facebook search engine, as well as in external engines like google. In the latter case the search was limited to pages within the domain facebook.com. As search strings, I used various terms that appeared in the names and self-descriptions of already identified pages. These included combinations of different modifications of the German word for "refugee" and "asylum seeker"[16], and of the German word for "shelter" or "housing"[17], or other typical slogans[18]. For each search, the highest ranked 1,000 results were examined and in case a new group was found, it was added to the list. That lead to a total of 168 groups.

Thirdly, following the snowball strategy that Caiani and Parenti (2013) used in a study of right-wing website networks, I used the "liked pages" section of each of the already identified pages to check for hyperlinks leading to other AAS-groups. This added another 18 groups. After that, I re-ran steps two and three to adjust for minor changes in the keywords due to the newly added pages. No new groups were found in this iteration. In a next step, the most recent 10 posts (and their comments, if any) on each group's page, along with the group's self-description (if any) was qualitatively evaluated to check whether each page matched the defined criteria. This simple check

16 i.e. "Flüchtling[e/s]", "Asylberwerber[in]", "Asylant[in/en]". I'd like to point out that especially the last term is clearly derogatory and only used among the political right. When it is repeated within this dissertation, this is purely for analytic reasons and by no means reflects my own standpoints.
17 i.e. "Unterkunft", "Unterkünfte", "Unterbringung[en]", "Heim[e/s]", "Hütte[n]", "Container"
18 "[city] wehrt sich/stellt sich quer" ([city] resists), "Bürgerinitiative [city]" (citizen's initiative [city]), "[city] sagt nein" ([city] says no)

confirmed that the posts actually discussed the topic of migration, asylum, and asylum-shelters in a negative way. This can be done by either posting text, linking to critical news reports, or posting images and videos that oppose refugees[19]. This inspection resulted in the exclusion of one clearly satirical page. In total, the procedure lead to a list of 185 AAS-groups, that was presented to and informally discussed with an external expert from the field of anti-racist NGOs, to confirm that no relevant actor was left out. After this multi-stage selection and verification process, I concluded that this list reflects the best attempt to compile a catalogue of groups that are of substantial interest to my case at the time of observation.

III-ii Research Questions

Having introduced the theoretical framework, an overarching question, and the case under study, I want to spell out more concrete research questions that unfold from this perspective and that can guide the processes data analysis, which is outlined in the following section. These questions reflect both a substantial interest in the so-far understudied case of anti-asylum or anti-refugee collective action processes and a theoretical interest in the application of the framework of Modes of Coordination to the study of digitally mediated protest. Very generally, the research questions that are informed by these interests can be split into four broad sets that each require different data or combinations of data and will structure the analyses in chapter IV of this thesis. The questions I seek to answer are thus:

[19] e.g. pointing to issues like crime, high costs, or institutional failure in relation to migration.

RQ-set I – What Anti Asylum Shelter (AAS) groups can be identified and what are their spatial and temporal activity patterns? How do these patterns correspond to a general interest in asylum-seekers and refugees and to records of offline AAS-activity?

RQ-set II – What are the topics that members of AAS-groups discuss and how are these topics discussed? Can collective identities of 'us' and 'them' be identified in these debates and how are these collectives portrayed? Can temporal patterns of topic prevalence be identified that correspond to those identified in the overall activity of AAS-groups? Are some AAS-groups closer in terms of a homogeneity of topics than others?

RQ-set III – How do AAS-groups use social media? What types of ties amongst AAS-groups can be identified and what networks evolve from these ties? How do the types of ties correspond to mechanisms of resource allocation and boundary definition among AAS-groups?

RQ-set IV – How do the types of ties identified combine into different Modes of Coordination of collective action? What properties of groups can explain their relational patterns, i.e. their mode of coordination? More specifically, does the proximity to formal organizations of the political right explain tie formation in different Modes of Coordination?

These sets of questions are not isolated blocks, but are instead entwined, overlapping, or flowing logically from each other. Nonetheless, each set focuses on a different aspect of the analysis and requires different sources of data or different analytic techniques. To further clarify this and lay out the structure of the analyses in chapter IV, the following section will elaborate on the different sources of data and techniques of collection and analysis that I employed to answer the research questions raised in this section.

III-iii Data and Methods

The following three sections will explain the methods of data collection, describe the different data-sets that will be used in combination, and briefly explain the family of methods that will be used to transform and analyze these data in order to answer the corresponding research questions. Before engaging in the details, Table III.1 gives an overview of the overall research design by broadly illustrating the links between each set of research questions, the data collected, and the methods applied.

Table III.1 Overview of research questions, data, and methods

Research Questions	Data Sources	Methodology	Chapter
RQ-set I	• Facebook Data on AAS-groups • AAS protest data • Google Trends	Description of time series and geographic patterns	Chapter IV-i
RQ-set II	Facebook Data on AAS-groups	Structural Topic Models	Chapter IV-ii
RQ-set III	Facebook Data on AAS-groups	Social Network Analysis	Chapter IV-iii
RQ-set IV	• Facebook Data on AAS-groups • Facebook Data on right-wing parties	Social Network Analysis	Chapter IV-iii

The detailed transformation, interpretation, or coding of data, the operationalization of concepts, the descriptive and inferential analyses, and the exact methodological techniques used for these will be discussed in detail in the analytic chapters that follow.

Facebook Data on AAS-groups

To obtain a Facebook dataset on AAS-groups, I collected data from each group on the list defined in the case selection. I used the Python programming language to write the

Sammlr[20] program (Hoffmann and Steimel 2017) that communicates with Facebook's Application Programming Interface (API) and retrieves the activities, meaning posts, comments, and reactions made on a set of pages at any time, together with a timestamp of the activity and, where applicable, the message text. This excludes cases of deleted posts or comments, or where privacy settings do not allow data to be collected via Facebook's API – this is why Facebook-data is characterized as "*curated self-presentations*" (Stier et al. 2017). To minimize the effects of deletions and exclusions, I collected data in two rounds (May 2016 and April 2017) and merged these sets. All in all, I collected 2,345,774 activities, 112,878 of which were posts, meaning status updates, links, videos, photos, or events. Posts can be commented on by users, with each comment containing a message – this was done 327,442 times in the data. Both posts and comments can receive reactions, usually in the most prominent form of a "like", but Facebook decided to give users the option to also express anger, astonishment and several other types of reactions in 2016. These reactions make up the remaining 1,905,454 activities (for a table and discussion, see chapter IV-I, pp.87-88). The script outputs a data-matrix, in which each row is one activity, and the columns hold the following information on each observation: unique page ID, unique user ID, timestamp, type (of post, comment, or reaction), hyperlink (if any), message (if any). Data was collected starting with the earliest activity found in each group and ending at the time of the second round of data collection in April 2017. The temporal

[20] Since Facebook has gradually restricted API-access in the last year(s), each application that researchers must register to run the Sammlr scripts (or any other script that accesses public page objects) has to pass Facebook's review process – to my knowledge, no research-data-collection-app (including Sammlr) has been successful in this. This means that data-vendors will gain an increasing role in this type of research and platforms like Facebook may restrict more and more what data will be made available to researchers or not. Freelon (2018) speaks in this context of a "post-API-age".

distribution of activity that will be discussed later in this thesis shows that this period captures the beginning, peak, and eventual decline of activity, thus making it unlikely to have 'missed' anything before or especially after this timeframe.

Additionally, the script collects data on page likes, i.e. those other Facebook pages, that a group's administrator recommends users to visit, advertised in a specific section of the front page called "Pages that this page likes"[21]. This way, page likes bear a functional resemblance to hyperlinks, that have been frequently discussed in the social sciences as used to *"create and maintain their personal or organizational ties online as well as offline"* (Park and Thelwall 2003), to build alliances and foster identity formation (Vicari 2014), and to lend structure to the networked public sphere (Kaiser and Puschmann 2017). Page likes were collected in the form of an edgelist for each of the 185 pages, where each row represents one like and the two columns contain the liking page's id and name (stable within each list) and the liked page's id and name. For each liked page, this page's likes were also collected to check for reciprocity of the relation, i.e. if a group that recommends another group via a page like is in turn also recommended by that page.

Lastly, the script collects a small amount of metadata on each group, namely the unique page ID, the page name, the group's self-description, the group's self-selected page category (e.g. "Community"), the page's logo picture, and the number of fans (i.e. individual users that liked this group).

These data on the activity of the 185 AAS-groups will be analyzed as a multiplex network (i.e. a network with different types of ties across the same set of nodes), in

[21] This must not be confused with the individual "like"-reaction mentioned above, with which each user can react to posts and comments.

which the edges are used to operationalize mechanisms of boundary work and resource allocation. Thus, these data will be used to answer the research questions in RQ-set III and partially RQ-set IV, using techniques of social network analysis (Wasserman and Faust 1994; Carrington and Scott 2011; Scott 2012). The textual data generated by the messages in posts and comments of each group will be analyzed as a corpus for quantitative content analyses, both to lend a 'thick' level of description to the case and to operationalize the structural patterns of content production as a mechanism of boundary work. Thus, these data will also be used to answer the research question in RQ-set II.

Facebook Data on right-wing Parties

To operationalize the proximity of each AAS-group to formal organizations of the political right and thus answer the research questions in RQ-set IV, I collected additional data on the Facebook pages of the two main right-wing parties in Germany, NPD and AfD. Parties are used as a proxy because they are highly formalized organizations with clear-cut memberships, accountability, formal decision-making processes, official spokespersons, and so on. Also, both parties are very active on Facebook, with the AfD even outperforming all other German parties in terms of Facebook activity (Stier et al. 2017). Data was collected analogous to the AAS-groups, using the Sammlr script to gather activities on the parties' activities from January 2014 until April 2017. The timeframe was limited to this (almost) three-and-a-half-year period to limit the amount of data, but also account for the period of main activity in AAS-groups and of the general debate on refugees and asylum-seekers in Germany. This additional dataset contains 7,076,387 observations on the AfD, 72,648 of which are posts, 675,372 are comments, and 6,328,367 are reactions as well as 4,430,876 observations on the NPD, 6,962 of which are posts, 287,784 are comments and 4,136,130 are reactions.

These data will be used to operationalize a variable of the proximity to formal organizations of each AAS-group in terms of their overlapping usership with each party. This will be analyzed using advanced techniques of social network analysis, like exponential random graph modelling to assess the impact of organizational proximity on tie formation in the AAs-groups' networks.

Regarding these data, I would like to briefly address the ethical issue of privacy and how I will handle data to assure compliance with ethical standards of social inquiry. While the data collected via Facebook's API come in the form of individually attributable activities on public pages and at the time of data collection, even users' names were available, I will not use or present any data on the individual level. Throughout the thesis, I will present and discuss my findings on the level of groups, thus aggregating individual activities to that level. In the case of network analysis, the sums of individual activities are used to construct ties among groups and to quantify their relative or absolute strengths, without making any single users' activity traceable. In the case of content analysis, the structural topic models used require individual message texts as the documents that make up a text corpus. Each text will be inputted without attaching a user id and results will be discussed on the level of groups and topics. When a single message or parts of it are quoted in a qualitative interpretation of a topic, it will usually be in the form of a translation and without identifying the author. To further ensure anonymity, I decided to not reveal the exact names of groups but opted for a coding scheme based on each group's geographical scope, that is described in more detail in chapter IV-i.

Offline AAS protest data

To allow for a more thorough description of AAS in Germany and their spatial and temporal patterns, and thus answering the research questions from RQ-set I, I collected data on demonstrations against asylum-shelters in Germany, using federal police records. In the repertoire of contentious actors in liberal democracies, demonstrations have become one of the standard forms of protest (Tilly 1977, 2013) and one that is usually acknowledged as a legitimate expression of policy preferences and as such protected by constitutional law. Two types of sources report protest against asylum-shelters in general and demonstrations in particular: firstly, the mentioned police records, secondly the “Mut gegen rechte Gewalt” (courage against right-wing violence) project, a joint project by the German weekly “stern”-magazine and the left-leaning NGOs Amadeu Antonio foundation and Pro Asyl that presents data in the form of an online “Chronik flüchtlinksfeindlicher Vorfälle” (Chronicle of anti-refugee incidents), collected by the two NGOs (Anon 2019; Benček and Strasheim 2016). In a study on the determinants of violence against refugees Jäckle and König (2018) used the chronicle to explore spatial and temporal variations, arguing that official police records come only in aggregated form. This is true only to some extend: the Bundeskriminalamt (Germany’s federal police) does publish data on violent incidents or demonstrations in aggregated form – however, members of the German Left-party (DIE LINKE) have used the parliamentary instrument of “Kleine Anfrage” (small inquiry) to formally request detailed information on demonstrations and violent attacks against refugee-shelters. The government’s answers to these inquiries are released by the Bundestag and contain disaggregated data on each demonstration or attack as recorded by the German federal police. For the purpose of this thesis, I will mainly focus on the analysis of demonstrations, as they are easier and more reliably verified, since they usually must be registered with the police. Further, Jäckle and König (2018) suggest that the study by Marbach and Ropers (2018), who gained access to disaggregated police records, found little discrepancy between police records and watchdog organizations' accounts. My own quick comparison between sources came to the same general conclusion on distribution patterns, despite differences in the number of cases. Therefore, I opted to use the official records as described above, made available by the German Bundestag (Bundestag 2014b, 2014c, 2015e, 2015f, 2015g, 2016b, 2016d, 2016a, 2016c, 2017a, 2017b, 2017c, 2014a, 2017d, 2018c, 2018a, 2018b, 2014f, 2014e, 2014d, 2015b, 2015a, 2015c, 2015d). Data from these sources was converted to a csv-file with the help of the tabula software (Aristarán 2018) and each entry was manually checked and corrected due to variations in the date formatting. For the demonstrations, each event was automatically geocoded using the Data Science Toolkit API (Warden n.d.), i.e. the free-text location of the police record entry was transferred into latitude and longitude to allow a systematic evaluation. In the case of demonstrations, the results of this coding were manually validated. In the case of criminal attacks, this step was omitted due to the high amount of work necessary and to the minor relevance for this study. In total, the data obtained contains 2,526 records of attacks on asylum shelters between 2014 and 2017, each coded with date, location, and type of offense. In the case of demonstrations, the data obtained contains 276 demonstrations against asylum shelters, each coded with date, location, title/motto of the event, and a police-estimate of the number of participants. Again, I want to iterate that the focus of this thesis is not on explaining offline events with online data or vice versa, let alone claiming causality, but rather on exploring a phenomenon in its wholeness and without the fallacy of an artificial dichotomy between ‘real’ and ‘virtual’. Therefore, these data will be used in comparative descriptions of temporal and spatial variation of online and offline activity to make informed claims about their similarity and thus additionally check whether the selection of online groups might or might not create spatial mismatches with street activity.

Chapter IV - Analyses

While chapters I, II, and III have outlined both the social and sociological relevance of this thesis, its theoretical angle, and its research design, the following chapter will present the empirical analyses that follow from this perspective on the study of our subfield of German Anti-Asylum-Shelter groups. These investigations will be loosely structured along the lines of the four different sets of research questions that were introduced in chapter III.ii (see also Table III.1). This means we will begin with a description of spatial and temporal activity patterns, followed by an analysis of content, and lastly by the investigation of networks of interaction. This strategy reflects various aspects of Charles Tilly's characterization of a field, which reads: "*fields certainly include spatial distributions of population or activity, but they also include temporal distributions and webs of interpersonal connections.*" (Tilly 2004:214). Thus surely, some of the choices in terms of data handling and analytic techniques may reflect individual preferences, but I nonetheless belief that the empirical investigation in the following chapter is both innovative and firmly rooted in social scientific perspectives.

IV-i Online and Offline Patterns in AAS Activities

Space

In this section, I will use the Facebook dataset on all 185 AAS-groups as well as the police records on AAS-activities to describe some characteristics and distributions, and to identify commonalities and differences. Some minor additional data will also be introduced to illustrate general public interest in issues of refugee-housing and to explore the temporal pattern of attention. This way, this section will seek to answer the research questions presented as RQ-set I, which I repeat here:

> *What AAS-groups can be identified and what are their spatial and temporal activity patterns? How do these patterns correspond to a general interest in asylum-seekers and refugees and to records of offline AAS-activity?*

Answering these questions requires us to translate free-text information on place into clear, unified, and comparable spatial information. This is the first transformation of raw data performed for my analyses and the coding scheme follows the convention of a two-character location code, either on the federal level ("DE" for Germany), where a group's self-proclaimed scope was Germany-wide, or of the level of a German Land (e.g. "BY" for Bavaria, "SN" for Saxony, etc.), where the scope was on a Land, a region, a city, or a city-district. Each location is followed by a two-digit identifier to distinguish between groups. This gives a clear, unambiguous, and anonymous code to every group that I will use in descriptions and analyses throughout the thesis. This step went hand-in-hand with an additional coding, in which I used the textual information on a group's scope to code longitude and latitude of that place. This could usually be derived from a group's name. In cases of ambiguous place names however, I conducted a content check of posts to derive an exact. Places with a wider scope than the municipal level (e.g. "Sächsische Schweiz") were coded with latitude and longitude of the geographic centroid of that region. Similarly, the three Germany-wide groups were coded to the geographic centroid of Germany, thus making them appear close to the Hessian-Thuringian border on a map. It must be noted, however, that there is no way to determine the actual location of individual users. We must therefore assume that users being active in groups with a localized focus are either living in that area, or at least show an interest in it, as they would otherwise have no interest in being active in that respective group. Indeed, research on SNS and locations have shown that users' online activity seems to correspond to their highly localized contexts and that their activities and interactions are usually a good indicator for their actual offline location (Cheng, Caverlee, and Lee 2010; Han, Cook, and Baldwin 2012; Wilken 2014).

The naming scheme along with the coded locations is illustrated in Figure IV.1, showing that these two coding schemes allow for a consistent, unambiguous naming pattern while at the same time revealing fine-grained geographic patterns. I used the R language (R Core Team 2018) for coding and the R-packages "sp" (Pebesma and Bivand 2005) and "spatstat" (Baddeley, Rubak, and Turner 2015) for mapping and analyses.

Figure IV.1 shows the administrative boundaries of the German Länder and the exact coded positions of all 185 AAS-groups, with slightly adjusted labels to avoid overlap. The fact that overlap cannot be prevented in some places, reveals a first finding, namely a nonrandom geographical pattern with a clustering of AAS-groups in the regions of Berlin-Brandenburg (labels: "BE" and "BB") and Saxony ("SN"). In other parts of Germany, like Mecklenburg Western-Pomerania (North-East) or Rhineland-Palatine and the Saarland (South-West), we do not find any such groups. Thus, while a majority of groups are located in the former German Democratic Republic (111), a non-negligible minority (62) of groups are in West-Germany[22]. This

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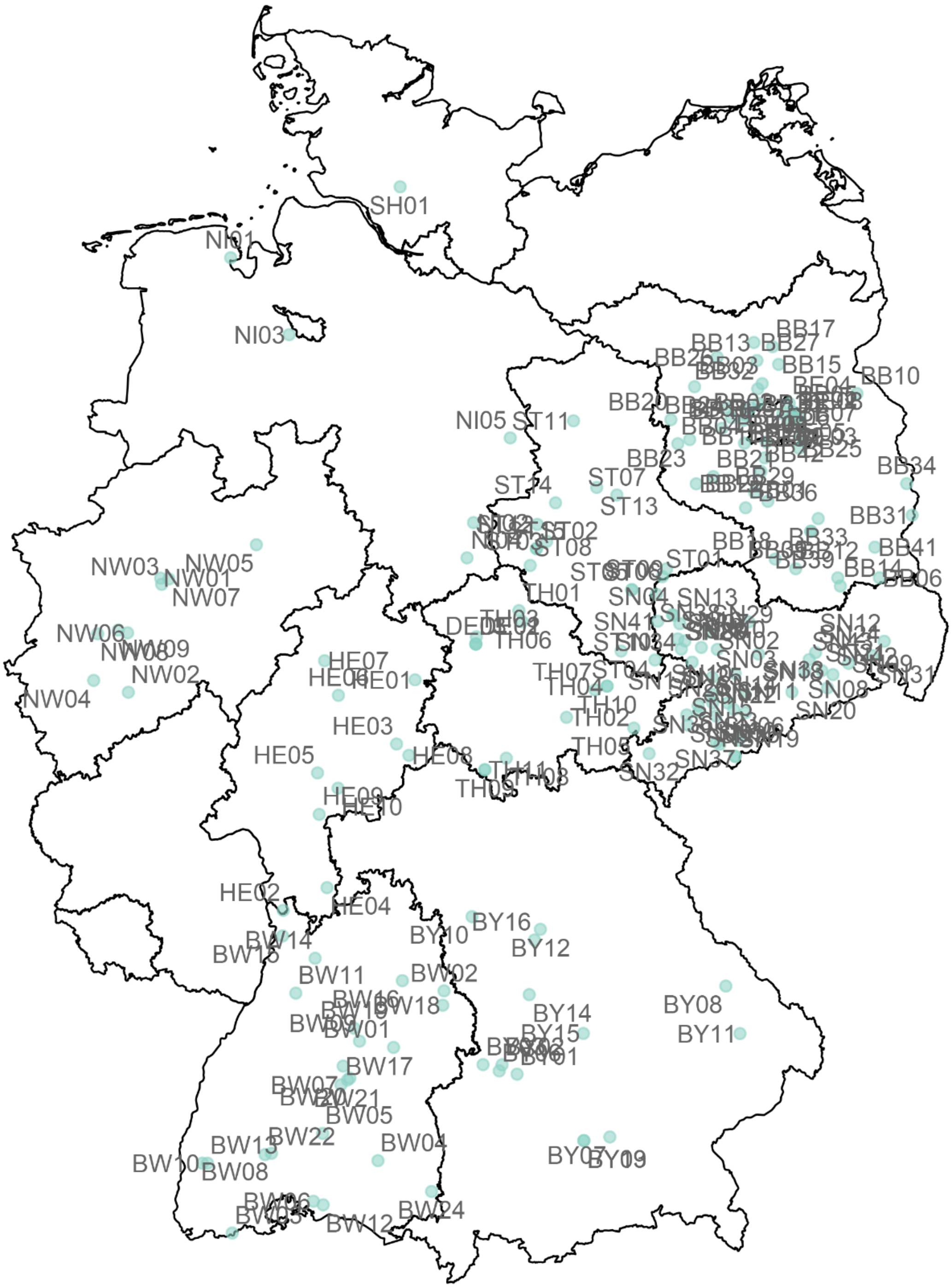
[22] Not counting nine groups in Berlin and three Germany-wide groups.

by and large confirms the pattern that Schelter and Kunegis (2017) found in a similar dataset.

Figure IV.1 AAS-groups' positions and labels



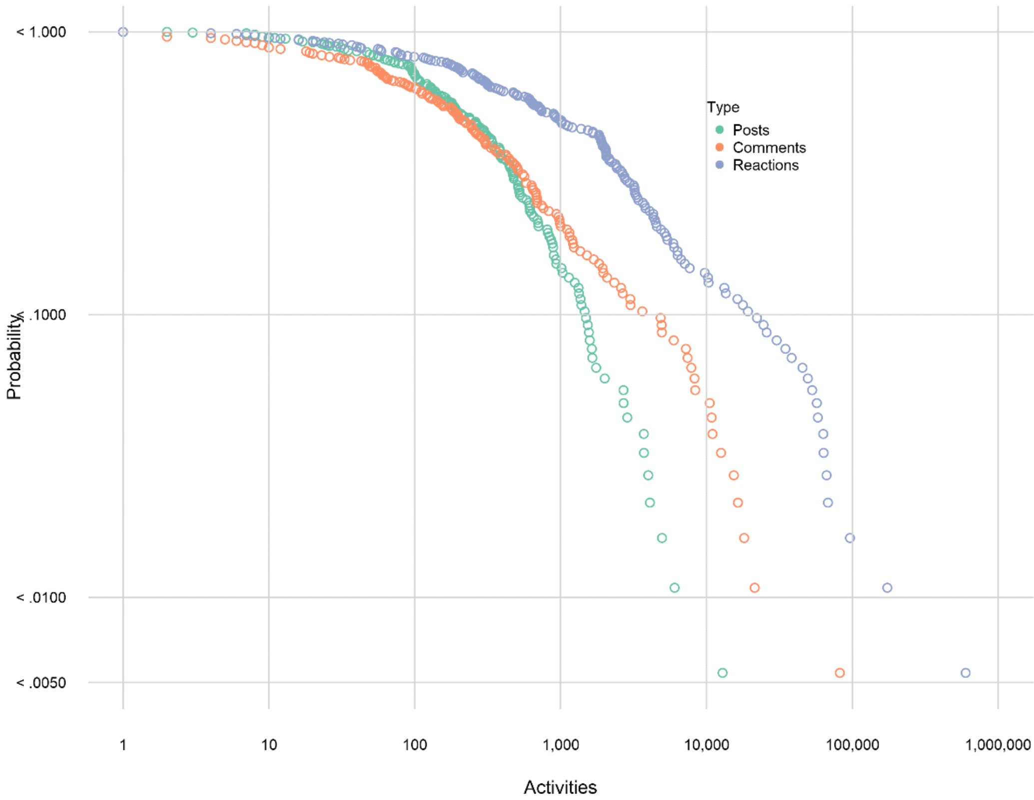
As Table IV.1 reminds us, the dataset is a collection of a total of more than 2.3 million activities. However, we must keep in mind, that these may be very unequally distributed across the different groups. This is visualized in

Figure IV.2, which shows the complementary cumulative distribution function (CCDF) of posts, comments, and reactions across the 185 AAS-groups.

Table IV.1 Total counts of activity types in AAS-groups

Activities	
Posts	112,878
Comments	327,442
Reactions	1,905,454
Total	2,345,774

Figure IV.2 Empirical complementary cumulative distribution function (CCDF) of posts, comments, and reactions across the 185 AAS-groups



This style of visualization is commonly applied when the aim is to explore and to compare distributions (Bessi et al. 2014). We can read the x-axis as the amount of activities of each type and the y-axis as the probability of finding at least this amount of activities on a given page. The doubly logarithmic axes reveal that even though the patterns for all three activity types are similar, the scales are different, meaning that the number of reactions by far outweighs that of comments and of posts. We can also see a sharp decline in probability for more than roughly 1,000 posts or comments on a page and more than roughly 10,000 reactions. The concentration of points between 10 and 1,000 posts and comments, or 10 and 10,000 reactions, means that on most of the pages, we will find activities within that range. However, we do find some outliers in the heavy tail of the distribution, meaning that the activity in very few groups by far outweighs the activity in many other groups. The similar distribution patterns of the three types of activities might be explained by a relation between the three types. Indeed, testing for rank correlation between posts, comments, and reactions all three combinations are significant with high values for Spearman's rho (>.8). In other words, groups that show high activities in terms of posts, also show high activities in terms of comments and reactions. From a perspective of social media affordances (Bossetta 2018; Halpern, Valenzuela, and Katz 2017), we can understand posts, comments, and reactions as the technological affordances offered by Facebook's architecture.[23] The fact that we see many more posts than comments and even more reactions thus can be understood in light of the fact that both effort and commitment differ by type of activity. In other words, posting requires certain amount of time and intellectual

[23] Although typically, affordances are discussed on the level of platform comparison (Bode and Vraga 2018; Stier et al. 2018) For a discussion on Facebook, see (Barrett and Kreiss 2019).

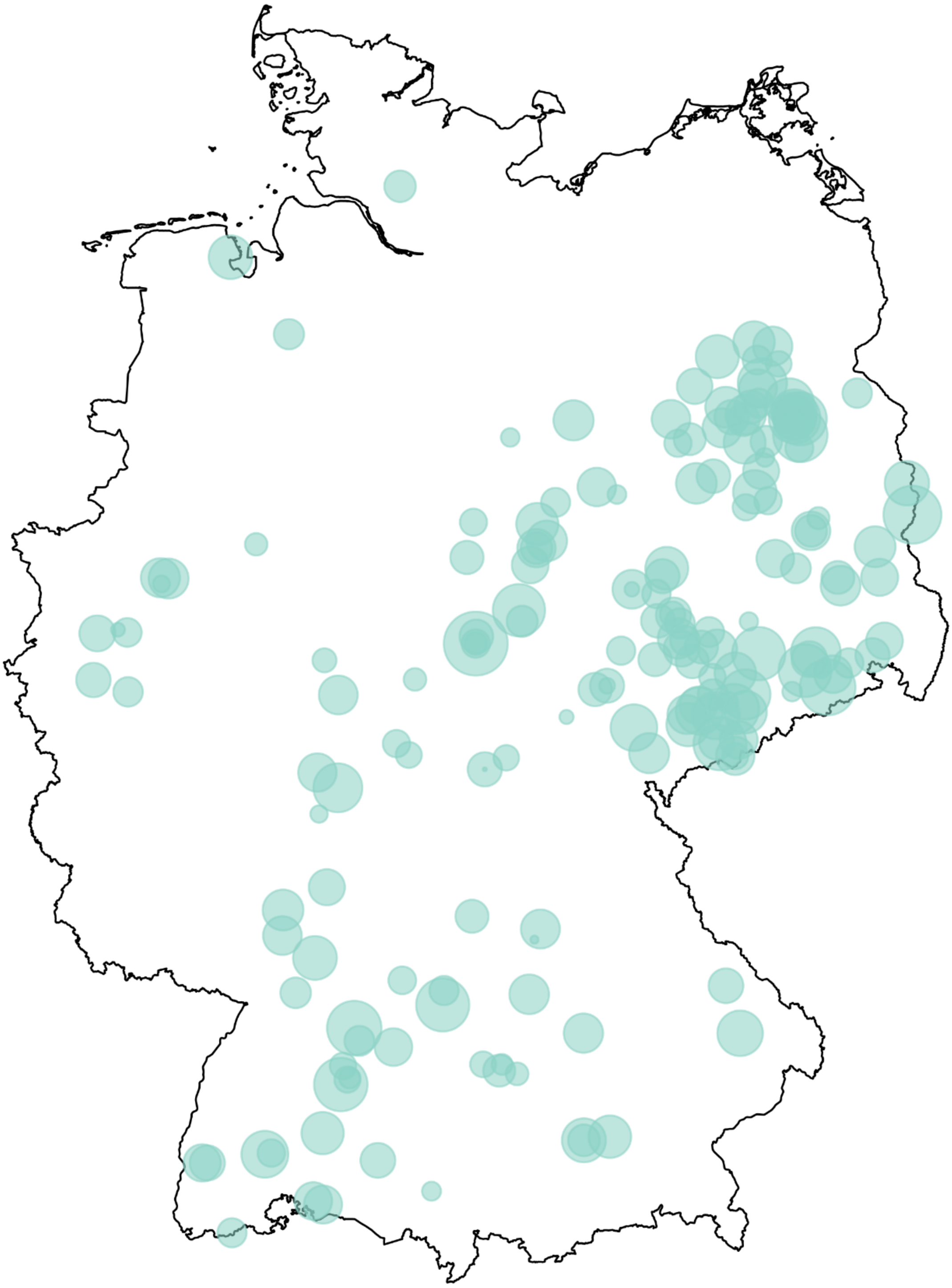
capacity on the user's side and might also be restricted to administrators in the technical side. Commenting however is reactive in nature and can rather signal the willingness to start or engage in a debate on content supplied by others. Reactions surely require the least commitment as they are basically one-click activities. Nonetheless, they have impact on recommendation algorithms and can increase visibility of content. In a study of Facebook audiences across German parties, Stier and colleagues speculate that a "like"-reaction on Facebook may be read as political support, while a comment may also be used to voice criticism (2017). However, both the fact that our study looks less at political competitors but at a more homogenous field than the party spectrum and the fact that we do not restrict our data to positive "like" reactions, speaks against this interpretation. Thus, a more detailed account of affordances might delve deeper into these differences and their empirical manifestations - from a perspective of Human-Computer-Interaction design, we might discuss the differences in sensory, cognitive, and functional affordance (Hartson 2003): For example, the animated smiling, frowning, or angry faces of emojis have a different sensory affordance than a post-button, with the former clearly assisting the user in understanding that these reactions may be used to express emotions. Of course, functional affordance also varies by activity type, as only posts can be categorized into events, photos, videos, etc., while comments are restricted to a (mostly textual) response to a post.

For us however, the fact that distribution patterns of each type of activity are remarkably similar suffices to aggregate them to a measure of overall group activity. Also, at this point, we remain purely on an aggregate level of group-activity and do not disassemble these into the individual users' contributions. In chapter IV-iii, we will discuss the question of membership and individual contributions in more detail.

Whether the differences between groups follow a geographic pattern can be examined in Figure IV.3. Analogous to Figure IV.1, all groups are represented by a green dot on a map, albeit with two differences: Firstly, to make the figure less cluttered, labels and borders within Germany are left out. Secondly, the size of each data-point corresponds to the base 10 logarithm of a group's total activity, as using a linear scale is not feasible due to the enormous difference in activity. This means that small differences in size must be interpreted as big differences in group activity.

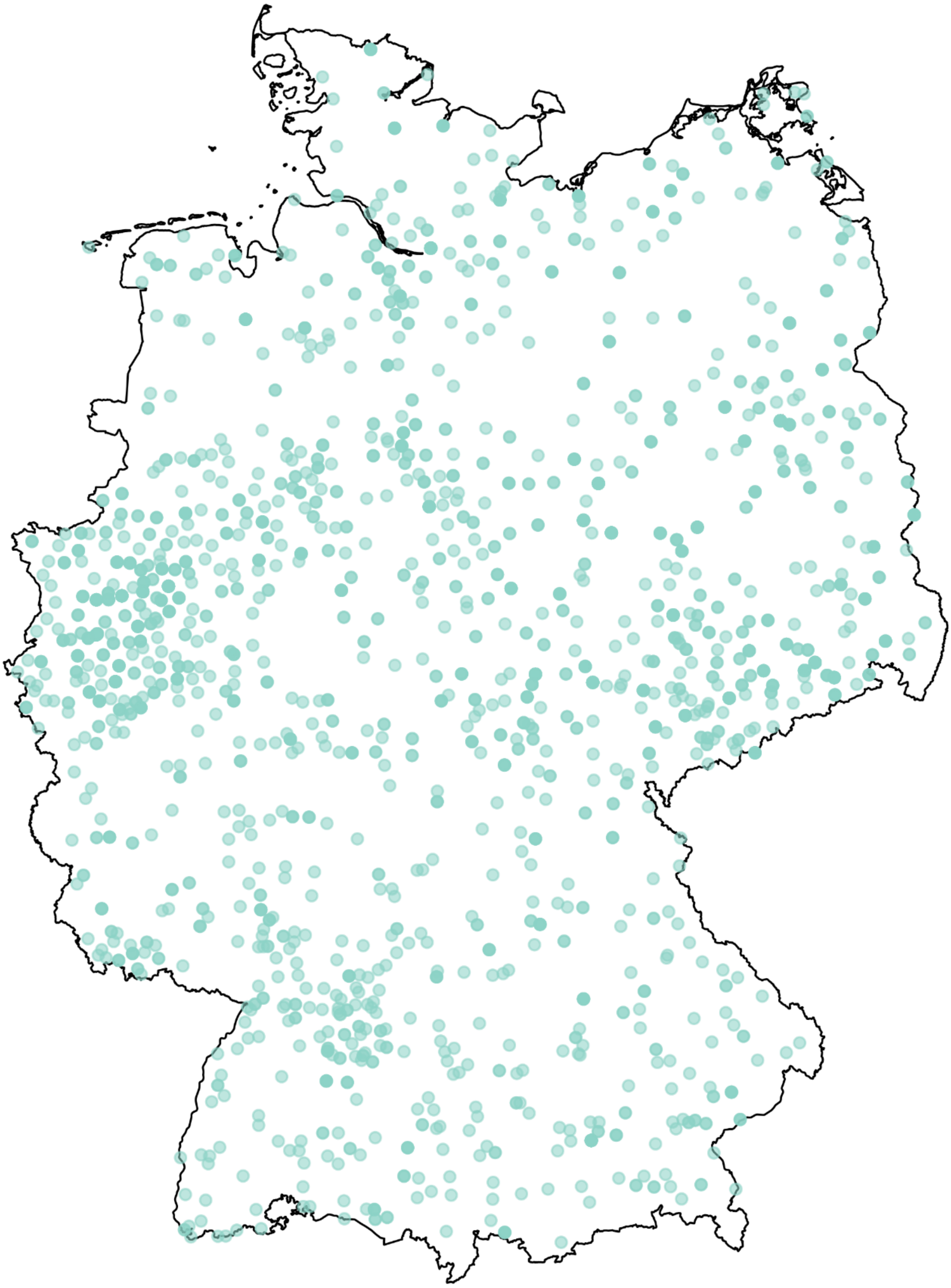
From a visual inspection, we can conclude that some of the highest activity groups are located in Saxony, Berlin-Brandenburg, and Baden-Wuerttemberg, while less activity is found in the West, the North, and the Southeast (Bavaria). In addition, one of the highest levels of activity can be found in the Germany-wide group in the center of the map. Thus, the key finding of this exercise is that the geographic pattern of group concentration in the East and South-West of Germany is further amplified by a concentration of activity within these groups. Later analyses of networked interactions will have to discuss whether these findings resonate in the importance or centrality of these groups within networks of collective action processes.

Figure IV.3 Regional scope (position) and observed activity (size) of AAS-Facebook-groups (N=185) in Germany



In a next step, I examined whether the identified patterns of spatial distribution correspond to the distribution of street activity. Figure IV.4 shows each attack against an asylum-shelter in Germany from 2014 to 2017. The data are collected from federal police records, as discussed in chapter III of this dissertation. In total, we see 2,526 attacks visualized on a map of Germany. Each attack is represented by a single point of light color, meaning that multiple attacks in the same place will lead to a more saturated dot. Attacks, as collected in this dataset, may range from showing a Nazi-salute, shouting racist insults, to damage of property, arson, or even attempted murder. All of them, however, are punishable crimes by German law, meaning unlike demonstrations, they constitute illegal (protest) activity. I include this figure to show that (a) while there are concentrations of attacks in places where we also can find AAS-groups, we can (b) nonetheless find many attacks in places without AAS-groups. Thus, the distribution of attacks does *not* seem to strongly correspond to the distribution of AAS-groups. To clarify these patterns and facilitate the visual interpretation, we can use spatial density plots of the point patterns, which can be found in the Appendix (Figure A.1). In addition, performing a test of Ripley's K-function (Dixon 2014), illustrates that crimes are slightly more clustered than expected by chance (see Appendix Figure A.2). Deeper analyses would have to take other factors like population density into account, as well as account for the fact, that attacks on asylum-shelters can only happen in the actual presence of such a shelter – on this, however, no comprehensive data exist.

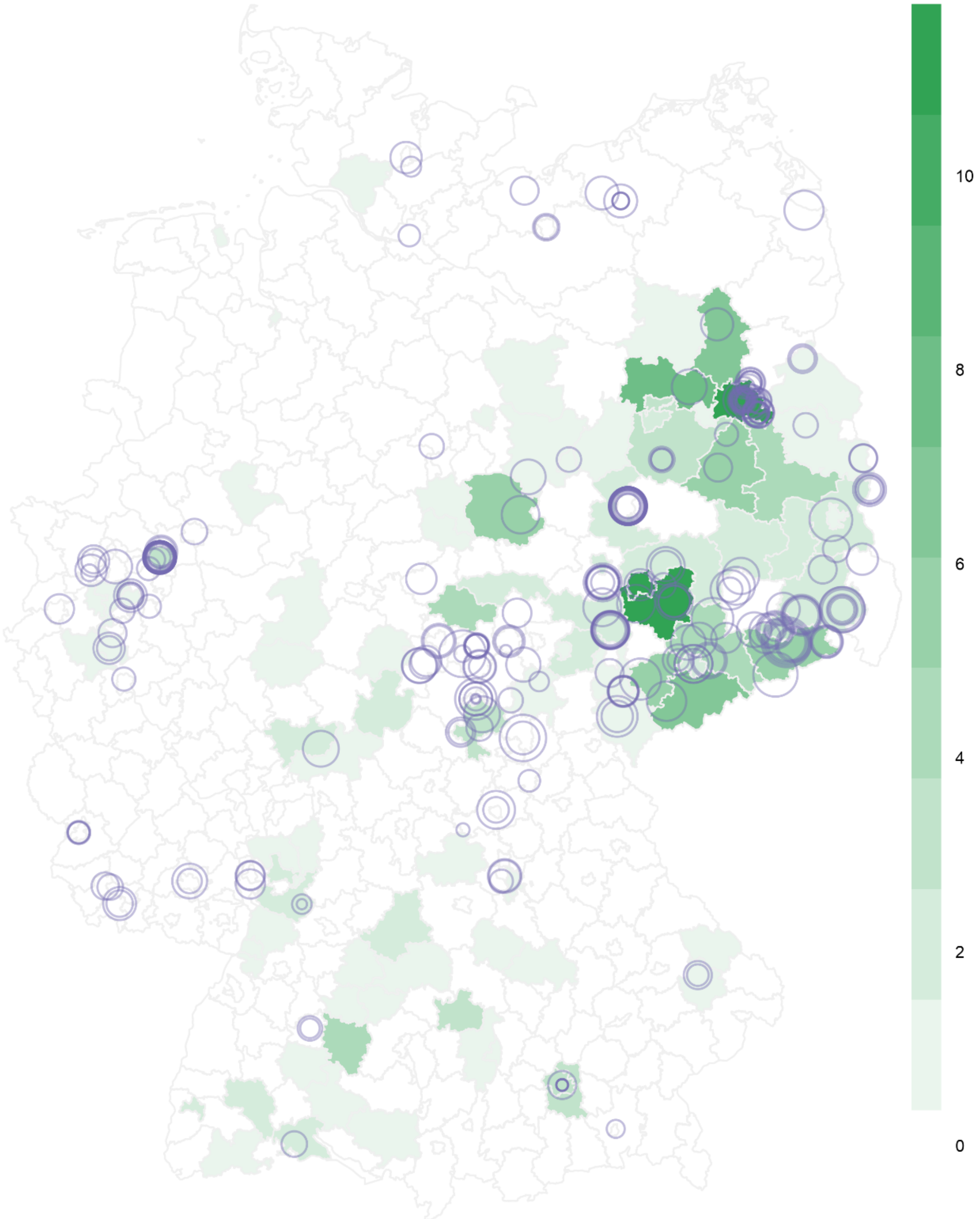
Figure IV.4 Location of attacks (n=2,526) against asylum-shelters 2014-2017



In addition, we must note that these attacks by definition may include political violence, which is linked to, but yet very distinct from more civil forms of collective action and protest. Political violence must thus be differentiated from other forms of protest (della Porta 1995; Tilly 2003). Della Porta (2008) has summed up the different perspectives that social movement scholarship has taken on the question of violence, including an organizational perspective that argues for different organizational properties and logics of clandestine and violent groups vis-à-vis more civic organizations. Thus, when showing demonstrations alongside attacks, we may both conceptually and empirically look at two very distinct phenomena. The discussion and visualization of attacks in this chapter thus rather serves to illustrate the sad fact that the phenomenon does exist in Germany, yet we can by no means conflate them with demonstration events. A perspective rooted in a genuine interest in political violence including an elaborate discussion on attacks and their determinants can be found in Jäckle and König (2018). For this thesis, it suffices to identify no strongly coinciding pattern between attacks and the presence of AAS-groups in a region.

This is different in the case of demonstrations, that are visualized in Figure IV.5. In this figure, we see multiple sources of data combined. First, the already familiar pattern of spatial distribution of AAS-groups is no longer visualized as points, but as the shading of each of the 403 German districts (NUTS-3 regions, in German “Kreise” or “kreisfreie Städte”). As the legend reflects, the shading varies by the number of AAS-groups that fall within each district.

Figure IV.5 Number of AAS-groups (N=185) per district (shading) and demonstrations (N=276) by number of participants (circles).



Thus, we find the same data as in Figure IV.1 and Figure IV.3, simply in different graphical form. The new information comes in the shape of purple circles, each representing one of the 276 demonstrations against asylum shelters that were held in Germany between 2014 and 2017, as described in chapter III-iii of this thesis. The size of each circle is proportional to the number of participants in that demonstration, as estimated by the police. Where no estimate was available, the average number of participants of all other demonstrations was used. The fact that we can identify intersecting circles or circles within one another shows that in many cases, multiple demonstrations were held in the same place during the observed period. Overall, the figure reveals a clear geographic similarity in the distribution of demonstrations and of online AAS-groups over Germany. Using Ripley's K-function test (Dixon 2014) with 49 simulations of complete spatial randomness, we can see that both demonstrations and AAS-groups are clearly and significantly more clustered than in a spatially random distribution.[24] Instead, they are more likely to be found, where there is also an AAS-group present, which is also visible in the spatial density plot in Appendix Figure A.1. To add to this visual inspection, I created a 403x3 matrix that recoded the presence [1] or absence [0] of (a) an AAS-group, of (b) a demonstration event, and of (c) a demonstration event drawn from a spatially random distribution of 276 events[25] for each of the 403 NUTS-3 regions. While there are more sophisticated methods available to analyze spatial data and account for the non-independence of observations, I believe that for our case, simple tests suffice to state whether an association between the observed presence of events and the observed presence of AAS-groups exists. While I ran a series of correlation and regression tests that all hinted at the same associations, I believe it suffices to conclude that the presence of an AAS-group is associated with the presence of a protest event (Cramér's V=.26), while this is less so when testing this association for spatially random events (V =.08) or for

[24] See Appendix, Figure A.2, for a visualization of the test results.
[25] Created with the "spsample"-function from the "sp"-package (Pebesma and Bivand 2005).

attacks (V=.13). This supports the visual impression given in Figure IV.5 and Figure A.1 and is in line with the findings of Vasi and Suh, who argue that both online and offline activity spring from the "*presence of energized activists*" (2016:150).

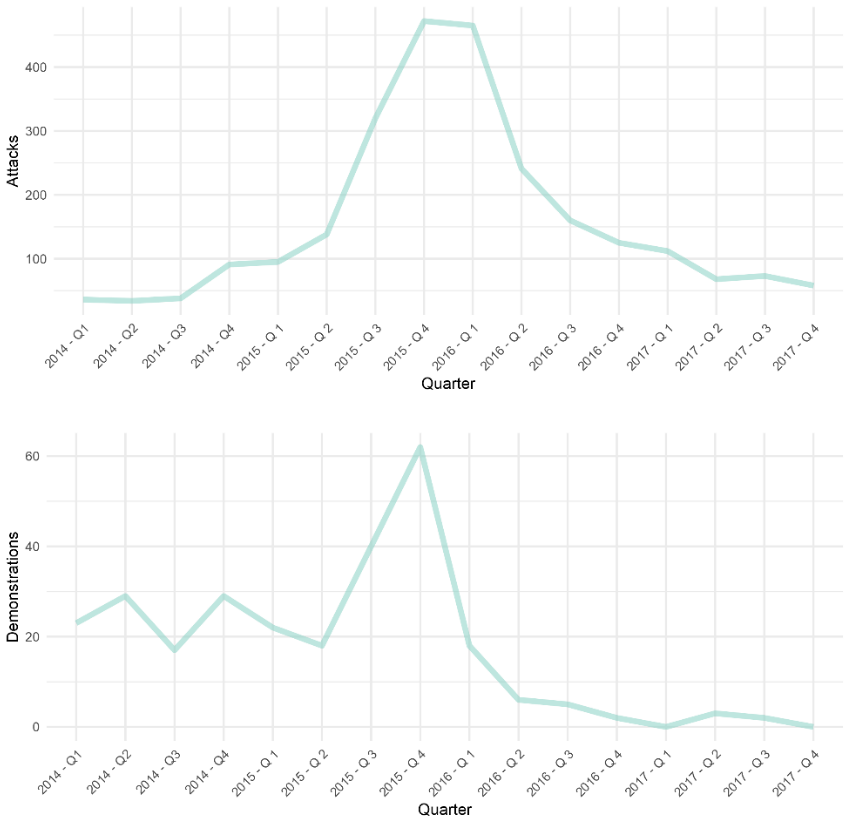
Additionally, we can find that 61 per cent of the demonstrations we observed were held in districts that also feature an AAS-group. In the case of a random distribution of demonstrations, this is true for only 29 per cent. Thus, most demonstrations were held in the vicinity of an AAS-group. Of those 39 per cent that fell outside of NUTS-3 regions with AAS-groups, most seem to have at least one AAS-group in neighboring districts, as Figure IV.5 suggests. Those that do not have a nearby group mostly lie in Mecklenburg Western-Pomerania (North-East) and the Saarland (South-West). Equally, the reverse is true, meaning we can only find few places where an AAS-group can be identified without a demonstration being held nearby at some point in the observation period.

We may speculate on directionality or even causality here, but for the sake of this thesis, it suffices to conclude that online AAS-groups and offline AAS-demonstrations are the proverbial birds of a feather. Thus, regardless of direction, there is a clear coincidence between the two. In turn, this means that in terms of identifying a population of AAS-groups, it is unlikely that a major group is missing and the assumption to have "captured" the phenomenon with the collected data is valid.

Time

After having identified clear spatial patterns in AAS activities, I will spend the next pages on a similar discussion regarding the second analytic dimension of this chapter: time. To continue with police records, I visualized both attacks (top) on asylum-shelters as well as demonstrations (bottom) against them in Figure IV.6.

Figure IV.6 Quarterly aggregation of attacks (N=2526, top) and demonstrations (N=276, bottom) against asylum-shelters in Germany

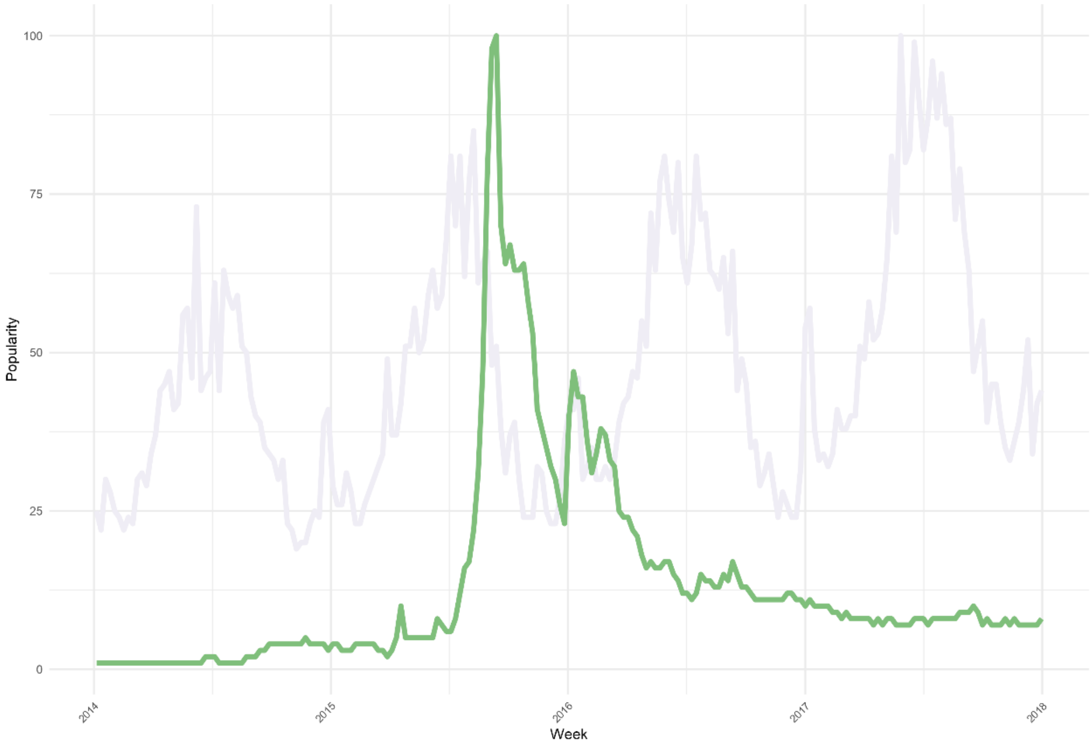


Data are aggregated to quarters of each year for a simpler visualization. First, we see a clear commonality in both the peak and the decline of attacks and demonstrations. Although on different scales, each rise in the fall of 2015 and peak in the winter from 2015 to 2016. This is well in line with the height of what was generally dubbed the "European refugee-crisis". In light of a humanitarian crisis among refugee's stranded in Hungary, the German government decided to take action in September 2015, organizing save passage to Germany for those in need and neglected by the right-wing Hungarian government (Blume et al. 2016). The "long summer of migration" had thus arrived in Germany and Chancellor Merkel's earlier words "We'll make it" ("Wir schaffen das") became the epitome of a policy that called out for solidarity and integration instead of isolation and demarcation. It is important to note that despite my rather grim focus on protest against asylum-seekers, the events of 2015 also saw a wave of solidarity sweep through German society and a (although short-lived) “Willkommenskultur” (Welcoming culture) could be identified at the time. Coming back to the opposite side, Figure IV.6 also tells us an important difference: While the records on attacks start from a relative low, demonstrations seem to have been a common sight in German streets even before their peak in 2015/2016. Thus, while this type of civic engagement was clearly amplified, it seems that already some organization was in place before, able to mobilize against asylum-shelters even in the absence of a major push-factor such as the general public debate on migration.

This becomes even clearer by a look at Figure IV.7, which shows the popularity of the German word for “refugee” (i.e. “Flüchtling”) in the google search engine from 2014 to 2017, normalized on a scale from 0 to 100 (google n.d.). Previous research on public attention and contentious topics has shown that search interest, as measured by these data, is a valid indicator of general public attention to a topic (Bennett, Segerberg, and Yang 2018). The green line shows that before the second half of 2014, public interest in refugees is virtually zero and remains comparatively low before a drastic peak in the fall of 2015. After that, interest starts to fall again, with a short relative peak in early 2016, right after the events surrounding the New Year’s celebrations in Cologne[26].

[26] In the area around Cologne’s central station and cathedral, groups of young men from predominantly Northern Africa and the Middle East sexually assaulted young women during the public New Year’s celebration. More than 1,000 criminal charges were filed against the alleged perpetrators, many of whom were registered as asylum-seekers (Anon n.d.).

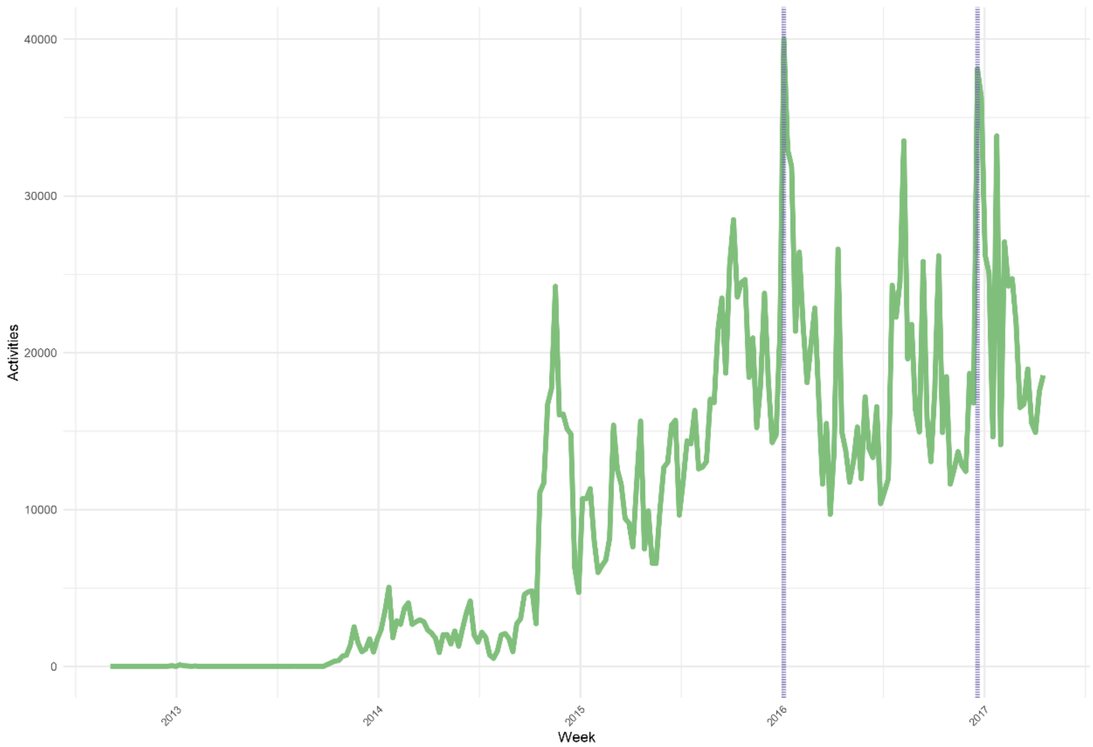
Figure IV.7 Popularity of the terms "refugee" (green line) and "weather" (gray background line) on Google over time



Despite a gradual decline in the course of 2016, the search term remains at a low but stable level of popularity. The light gray line in the background visualizes the same measure of popularity for the German word "Wetter" (i.e. "weather"), to illustrate the typical level of variation (in this case, seasonal variation) of a "neutral" search term on google. Against this background, it becomes even more apparent, how suddenly and massively, a previously almost nonexistent public interest in the topic of refugees and asylum-seekers was generated and how key events resonate in the behavior of information-seekers online.

These key events also leave clear marks in the activities of AAS-groups, as Figure IV.8 illustrates. Shown here is the weekly total count of all activities between September 2012 (the earliest activity recorded) and April 2017 (the end of data collection). The two highest peaks correspond exactly to the timing of the already mentioned events in Cologne (31.12.2015/1.1.2016, first vertical line) and the terrorist attack on a Christmas Market in Berlin (19.12.2016, second vertical line) [27].

Figure IV.8 Weekly total activities of AAS-groups



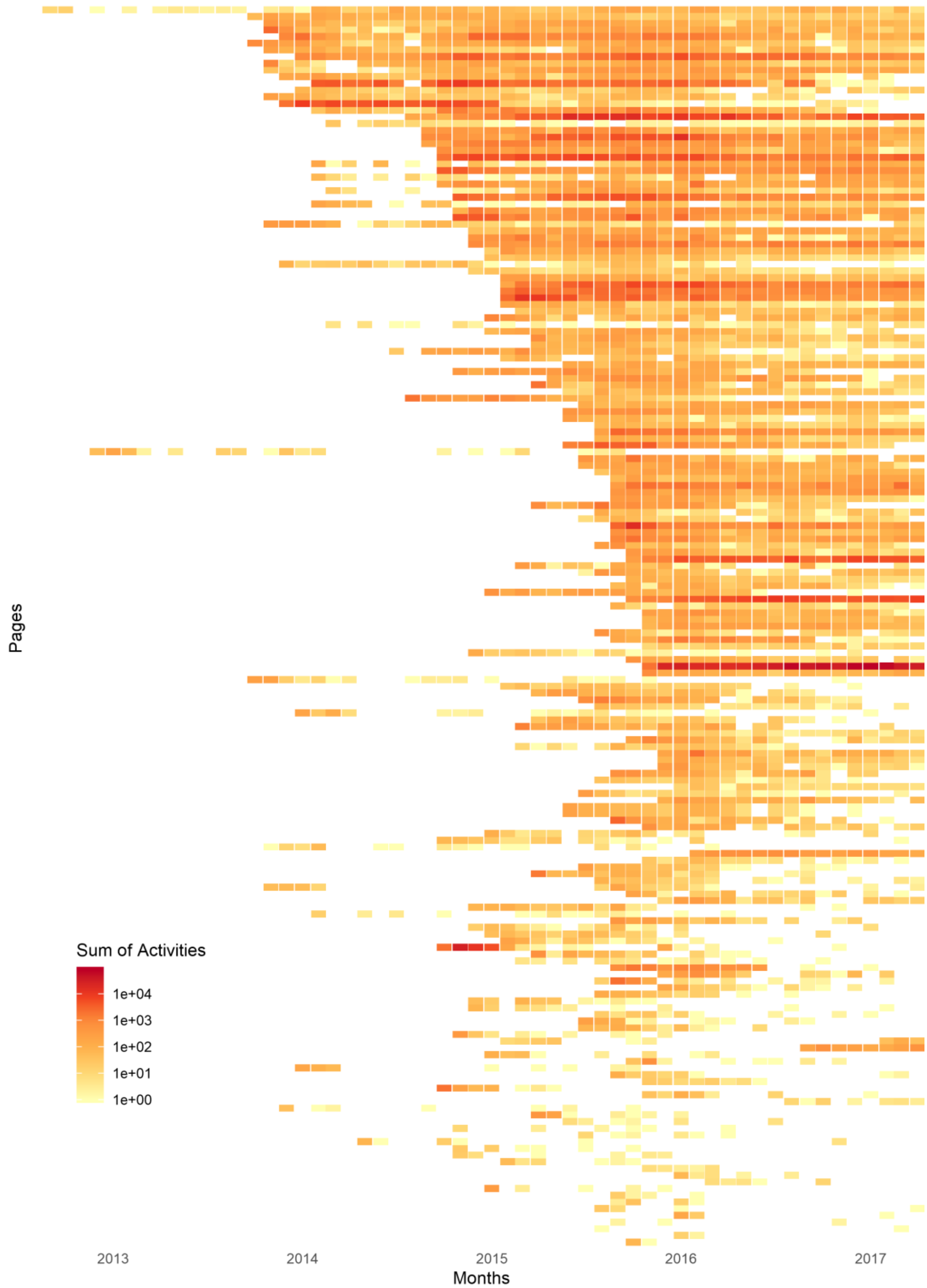
Despite the similarities, some important differences to the data on public attention can be identified. First, we can already see peaks of activity in late 2013 and even more so during the year 2014. While activity rises in the fall of 2015, this incline is not as drastic as in the general public interest, meaning that to people active in the AAS-community, the height of the so-called "refugee-crisis" does not demarcate such an enormous exogenous shock. Thus, within these groups, people must have been already well aware of the issue and unlike public interest, their activities were not sparked by the events of 2015, but were already well underway. In this regard, the activity pattern

[27] Tunisian Islamic State (IS) terrorist Anis Amiri killed twelve people and wounded 55 in a terrorist attack at Breitscheidplatz in central Berlin. Earlier, Amiri had (unsuccessfully) applied for asylum in Germany. Four days after the attack, he was shot by the Italian police in Sesto San Giovanni.

of AAS-groups shows commonalities with the data on demonstrations against asylum-shelters, as seen in Figure IV.6. Due to a lack of data in police records, we cannot make claims about the period before 2014, but it becomes clear nonetheless, that both AAS-activity and demonstrations were already happening throughout the year 2014. Thus, both did not need public interest as an initial condition - although it may well have served as an amplifier. Also, unlike general public interest, AAS-groups' activity does not die down as fast but remains at higher than the pre-2015 level throughout the period of data collection. This is also in contrast to both forms of offline activity, shown in Figure IV.6. We may thus reasonable speculate that whatever the exact nature of the relation between online and offline AAS-activity in its initial and its peak phases, the pattern clearly diverges in the course of 2016.

However, the view on temporal patterns of AAS-activity so far has aggregated activity over all 185 groups, ignoring different dynamics across these groups. However, as Figure IV.3 has shown, groups vary in their degree of activity. That these differences must not be ignored, is illustrated in the heatmap in Figure IV.9. The visualization is based on a matrix with the dimensions 55x185, with each cell containing the count of activities for each of the 185 groups in each of the 55 months of observation. The gradient coloring reflects the log-value of that count, ranging from no activity in white to a dark red for the highest activity by any group in a month.

Figure IV.9 Heatmap of monthly activity by group



The order of groups from top to bottom reflects the aggregated activity of each group over the entire period and shows that the top groups in terms of total activity are not necessarily the ones who have the highest monthly values, but who have been active for prolonged periods of time. The heatmap reveals that AAS-groups can be very heterogeneous in their activity. On the one hand, the count of monthly activity varies greatly, making a log-scaling appropriate. On the other hand, different temporal dynamics may be observed. We can identify groups that have been active early on and keep being so throughout the period of data collection, but we can also identify groups that are active only occasionally and groups, whose activity stops suddenly or peters out over time. The reasons for this may be manifold: In some cases, activity might not have picked up the desired dynamics, Facebook might have deleted a page due to rule violations[28], the original grievance (i.e. shelter) might have turned out not to be built in the first place, or people might have simply lost interest. In other cases, we observe opposite: instead of dying down, activity increases in the later periods, well after the general peak of activity in late 2015[29]. This may speak for a certain polarization within this episode of contention (McAdam, Tarrow, and Tilly 2004), in which some groups or individuals opt out of contentious activity, possibly feeling represented by the parliamentary force of the newly emerging AfD, while others become even more active in the remaining groups. It may also mean that we observe a process of monopolization or centralization evolving among AAS-groups, in which more and more activity is coordinated within one group, rather than across groups. These assumptions on the base of activity patterns remains speculative at this point, inviting

[28] However, this is not the most likely case, as Facebook at the time had not been very active in policing the platform. Also, many of the observed groups have been very active in spreading hate without being deleted.
[29] Figure A.3 in the Appendix shows the time and the value of each group's peak of monthly activity, as well as their average daily activity. This reveals that indeed some of the highly active groups are late-peakers.

deeper analyses of content and networked interaction among the groups, to solve these puzzles. When reading this figure in conjunction with Figure IV.8, it becomes clear that the different peaks and dynamics in the latter figure are driven by different mechanisms. While the rise and peak of total activity during 2014 and 2015 seem to reflect a widening of the field of AAS-groups, with many new groups being initiated, the peaks and constantly high activity throughout 2016 and 2017 seem to reflect a narrowing of the field, with activity more or less centralized in a small number of groups.

Chapter Summary

This (sub)chapter aimed at a descriptive analysis of temporal and spatial patterns of online and offline AAS activities. I have introduced some of the properties of my main dataset on Facebook-groups, as well as some supplementary data from police records and, to a smaller extend, from google search trends. These served to answer the research questions from RQ-set I that asked for distributions of and correspondence across these data sources. In terms of *space*, it could be shown that there are clear and non-random foci of AAS-activity, that correspond strongly to the foci of AAS-demonstrations, but not so strongly to attacks on asylum-shelters. In terms of *time* it could be shown that there are clear patterns of AAS-activity, in terms of a similar peak of activities in online and legal as well as illegal offline AAS-activity, and in the general interest in the issue of refugees. However, differences emerge through a closer look at the period before and after the height of the so-called “refugee-crisis”. Demonstrations and online activity were already under way throughout 2014 and the latter continued on a high level long after the general public interest in these issues faded. A look at the temporal distribution of activity across groups also revealed that overall activity may be driven by different mechanisms, laying out some of the puzzles to be solved in the more in-depth analyses that follow. Therefore, we will move on to an analysis of the content that is produced through the writing of posts and comments within AAS-groups. We will thus disassemble (some of) the activities we have so far treated as an aggregate into different topical discussions. This serves not only to understand better what these activities actually mean, but also how these topics change in the course of time and in light of external events. The following chapter will present the data, methodology and results of this exercise.

IV-ii Content Analysis

The purpose of this chapter is twofold. On the one hand, a substantial interest stems from the exploratory approach aimed at a Weberian “verstehen”, meaning to add substantial knowledge to the case under investigation. This aids our understanding of the nature of German AAS-groups and their issues, claims, problem definitions, and self-ascriptions. On the other hand, the analysis of content is instrumental to the following chapter on networks, meaning that the commonalities of groups in terms of their framing of a collective identity will serve as an indicator of the mechanism of boundary work, used to operationalize the Modes of Coordination framework. In the design of this thesis, this section corresponds to the research questions presented as RQ-set II, which I repeat here:

> *What are the topics that members of AAS-groups discuss and how are these topics discussed? Can collective identities of ‘us’ and ‘them’ be identified in these debates and how are these collectives portrayed? Can temporal patterns of topic prevalence be identified that correspond to those identified in the overall activity of AAS-groups? Are some AAS-groups closer in terms of a homogeneity of topics than others?*

I will seek to answer most of these questions within this chapter, with the notable exception of the last question. The answer to this question will be based on the results of the content analysis yet will be analyzed as one type of tie in a network of AAS-groups and thus find its answer in the chapter on networks and Modes of Coordination. Since I decided to group research question by data-sources, I nonetheless keep this question within RQ-set II.

Data

The data used to answer these questions are the textual contents produced by users in their engagement with AAS-groups, meaning the actual messages people wrote in posts or comments. Table IV.2 sums up some of the basic properties of the textual data at hand. In theory, every post in Facebook's data structure can contain a message, but in practice, not all do. Posts are of different types, the most common of which are status, link, photo, and video. For many types of posts, it is possible, but not necessary to include a brief accompanying message, i.e. in cases where photos and videos are meant to speak for themselves. As we read in the table, however, 390,130 or 89 per cent of the 440,320 posts and comments do contain a message text (reactions, the third type of activity, never do). In total, I counted more than 9.7 million words, with the average words per message being 25. The median however is 13, meaning that half the message texts in the data are shorter than this.

Table IV.2 Textual data description

Textual Data	
Posts + Comments	440,320
- Containing Messages as Total	390,130
- Containing Messages as Fraction	.89
Total number of words	9,738,801
Average words per message	25
Median words per message	13

This overview illustrates a number of things: Firstly, we can identify a tendency towards short texts, which does not come as much of a surprise, given that the logic of Facebooks follows a structure of original input (posts) and users sharing their (often short) thoughts on this input (comments). Secondly, we can see that in the majority of posts, we can find written messages. This is non-trivial, as the analytic approach taken in this chapter, focuses solely on text, ignoring the audiovisual possibilities of the medium. The reason for this is the complexity of an integrated approach of analyzing text, photo, video, and audio and the limited methodological tools of doing so. Given the constraints of a dissertation, I opted to focus solely on text. Therefore, it is important to know that text is central, as even in the given multimedia environment, many audiovisual pieces of content are accompanied by a written contextualization. Thirdly, the overview shows that the amount of textual information leaves but two methodological choices: sampling the data for a 'manual' approach or relying on automated approaches to content analysis. I chose the latter path and decided to use techniques of topic modelling to work with the given data.

Method

Topic models are a set of quantitative tools to uncover the latent thematic structure of large corpora of texts. More specifically, probabilistic topic modeling algorithms are *"statistical methods that analyze the words of the original texts to discover the themes that run through them, how those themes are connected to each other, and how they change over time"* (Blei 2012). The most common form of topic models uses latent Dirichlet allocation (LDA), which is *"a three-level hierarchical Bayesian model, in which each item of a collection is modeled as a finite mixture over an underlying set of topics"* (Blei, Ng, and Jordan 2003). In other words, each document, i.e. observed piece of text like the message of a post or a comment, contains a number of terms, i.e. the single words that make up this specific document and that may be shared with other documents. The latent topics are distributed over these terms and identifying and interpreting these topics means uncovering the more or less hidden structure of the corpus, i.e. collection of documents (Grimmer and Stewart 2013).

Thus, statistically a topic is nothing but a probability distribution over each word of the corpus and a document is nothing but a probability distribution over topics. Therefore, the aim of LDA is to estimate the two matrices β with the dimensions of K topics and V words and θ with the dimensions of K topics and D documents. What we want to know are thus the probabilities for each term to appear in a topic and for each topic to appear in a document (Blei et al. 2003; Maier et al. 2018). Before the estimation of these matrices, Bayesian statistics assumes a prior Dirichlet distribution of probabilities. Starting from randomly assigned document-topic and term-topic probabilities, LDA then *"aims to maximize joint likelihood of the model by iteratively adapting values of the word-topic distribution matrix φ and document-topic distribution matrix θ"*(Maier et al. 2018: 96). Thus, the outcome of a topic modeling process with LDA are basically two matrices, one informing the researcher about key terms that make a topic interpretable and another that informs about how topics co-occur in documents. That being said, it is obvious that topic models are so-called *bag of words* approaches meaning they do not discriminate between types of words like for instance Quantitative Narrative Analysis would (Franzosi 2010) and do not care about the positions of words within a sentence, like N-Gram Analysis would (Cavnar and Trenkle 1994). While I do not find it useful to dig deeper in the technical and statistical aspects underlying LDA here, it is worth mentioning that no common substantial or theoretical definition of the concept of *topic* exists (Maier et al. 2018). As mentioned, statistically topics are distributions, yet an application of this technique in the social sciences and a substantial interpretation of its results require an understanding of what topics actually mean in a given context. As a relatively new and still developing group of methods from the fields of machine learning and automated text classification, this shared meaning and theoretical reasoning in the social sciences is still lacking. According to Grimmer, who studied U.S. Senators' press releases, topics represent *"politically relevant concepts"* (Grimmer 2013:627), assuming that concepts like health-care or war will be talked about using different terms (Grimmer and Stewart 2013). In an application of topic modeling to scientific journals, Günther and Domahidi stress that topics remain vaguely defined in scientific debate and offer a tentative definition of topics as *"general themes that authors write about"* (2017:3057). Geese applied topic models to study political speeches on immigration, suggesting that topics in this context represent the *"latent issue attention of speeches"* (2019) that may shift over time. Stier et al. (2017), who used topic models to study Facebook activities of German parties and populist actors, argued that similarity in terms of topic distribution can be seen as debating the same issues, showing that discussing similar things in similar terms reflects the ideological and political proximity of (collective) actors. Thus, I follow this general understanding of topics representing substantive issues of interest to actors, in turn meaning that debating the same topics not only reflects but also fosters a common identity. To allow topic probability to vary over time and across actor groups, a modification of the basic LDA topic model is required. For this purpose, topic models have been developed that are dynamic (Blei and Lafferty 2006), correlated (Blei and Lafferty 2007), hierarchical (Teh et al. 2006), or factor in the order of words in a sentence (Wallach 2006). For the purpose of this thesis, in which I want to include the 'who' and the 'when' of each message, I will rely on the approach of Structural Topic Models (STM) (Roberts et al. 2013; Roberts, Stewart, and Tingley 2016), which *"accommodates corpus structure through document-level covariates affecting topical prevalence and/or topical* *content"* (Roberts et al. 2013:1). In other words, metadata such as time or authorship, political leaning, etc., can be added on the document-level and are allowed to explain topic prevalence and topic content. Thus, STM move topic models beyond mere classification and exploration towards social scientific applications that call for inference. As my research questions ask for temporal patterns in the debates within AAS-groups and for similarities between groups in terms of these debates, STM is an ideal methodological choice for my type of data and research questions[30]. Another practical advantage of STM is that they come with an implementation in the R statistical language and a number of accompanying packages to aid visualization and interpretation.

Preprocessing

Thus, the data that I used to input to the topic model include the message text of both posts and comments. These texts were not fed into the model in their raw form, as communication via SNS tends to be informal, thus containing undesirable noise that requires careful cleaning and preprocessing before data can be used in computational analyses (Lucas et al. 2015; Maier et al. 2018; Reber 2018; Welbers, Van Atteveldt, and Benoit 2017). For example, some users may decide to write in capitalized letters, while others use only lower-case. For a case-sensitive algorithm, an otherwise identical message written in either upper- or lower-case would consist of entirely different terms. Further, topic models care only about the *terms* nested in documents -

[30] Note that STM differ from LDA also in their deterministic nature and non-random initialization procedure. This produces slightly different but more reliable results even in the exploratory part of the topic model. As these details are highly technical, the above introduction to topic models has focused mainly on LDA as the most used implementation to illustrate the general purpose and use-cases of this family of techniques.

punctuation, symbols, and graphical characters like smileys that are frequently used in informal digital communication, are of no use to the model. Therefore, using the R environment (R Core Team 2018), the following steps of cleaning and preprocessing were applied to the original message texts: *Firstly*, the texts from each post and the associated comments were collapsed into one string. The rationale behind this step is to avoid problems associated with shorter texts in topic modeling by assuming that comments to a post are very likely to reflect user opinions on the post's matter and a group's discussion of that issue. This accounts for the fact that comments and posts form one thread of conversation around an issue. From a qualitative observation of the produced content, comments were usually used to express approval of a post, rather than express dissent or provoke controversial debates. There are several advantages to grouping posts and comments into one document. Firstly, comments do not stand alone, but are put into exactly the context where they were meant to be, thus making each document with comments a "co-authored" piece, which is thus allowed to contain multiple opinions. Secondly, reducing the number of documents greatly reduces computational efforts, as the dimensions of the document-term-matrix are vastly reduced. *Secondly*, all characters in the corpus were converted to lower-case. On the one hand, this introduces a certain amount of ambiguity, especially in the German language. On the other hand, one of the benefits of this standard procedure (Lucas et al. 2015; Maier et al. 2018) is that especially in cases with very irregular spelling and use of capitalization like messages on SNS, unification to lower-case will help stop word removal and lemmatization. The look-up dictionaries used in these steps will have correct capitalizations only and would thus fail to detect words that are wrongly and irregularly capitalized. For example, a comment like "Wir Wollen KEINE

Asylanten in UNSERER stadt!" ["We don't want asylum-seekers our town"] will cause problems, as all but two words in it are wrongly capitalized. Therefore, lower-case conversion is recommended as a first step of preprocessing by Maier et al. (2018), who have systematically reviewed different accounts of topic modeling in scientific publications. *Thirdly,* hyperlinks were removed from the text, using a regular expression[31] that detects all http or ftp links. *Fourthly*, symbols and graphical characters like emojis, all punctuation, and all numbers were removed using regular expressions[32], as they do not constitute terms in the sense of topic models. *Fifthly*, stop words were removed, using a comprehensive archive of 621 German words (Diaz 2016) and adding another 26 custom words[33], that were not included in the archive. All stop words were also converted to lower case to match the corpus. In automated text analyses, stop words are considered terms that are frequent in a language, yet contain little substantial meaning, as they are not specific to the content the researcher wants to analyze (Maier et al. 2018; Reber 2018; Welbers et al. 2017). In English, typical stop words would be "the", "and", "or", etc., that appear in almost every text and thus add no exclusive meaning to a document. As topic models use a document-term-matrix, it is also desirable in terms of computational resources to keep the dimensions of this matrix small by excluding stop words prior to any computation. Nonetheless, as Lucas et al. (2015) argue, the choice of stop words is a substantive decision and researchers should check, whether any out-of-the-box stop word list does contain seemingly insignificant terms that might carry a specific meaning in a given

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[31] Pattern: "?(f|ht)(tp)(s?)(://)(.*)[.|/](.*)"
[32] Patterns: "[^[:graph:]]", "[[:punct:]]", "[[:digit:]]"
[33] "dass", "mal", "schon", "war", "beziehungsweise", "bzw", "vielleicht", "vllt", "ma'", "heute", "gerade", "erst", "macht", "eigentlich", "warum", "gibt", "gar", "immer", "schon", "beim", "ganz", "dass", "wer", "mehr", "gleich", "wohl"

research context. *Sixthly*, words containing less than four characters were removed. The reasoning behind this is the same as in stop word removal, meaning to keep the document-term-matrix small by assuming that short words are unspecific of a document's content (Reber 2018). These may be exclamations like "oh" or "aha" or abbreviations like "mE"[34] (in German used for "in my opinion") that are too infrequent to appear on a list of stop words. *Seventhly*, any whitespaces, leading, trailing, or in between terms was removed, as it obviously contains no information. *Eighthly*, messages that now contained less than five words were removed. Short documents are assumed to contain little information and variation, and matrices with the number of documents as one dimension will thus be smaller and hence reduce computation time. Further, short texts are problematic for topic models as their document-term-matrix is hence very sparse, and little co-occurrence is possible if a text contains too few words (Yan et al. 2013; Zhao et al. 2011). *Ninthly*, one of the most problematic steps in preprocessing was performed, namely the lemmatization of each term. In written text, declension and conjugation cause many words of the same root to appear in different variations, yet all referring to the same phenomenon. For example, a German user could speak of refugees as "Flüchtling", "Flüchtling**s**", Flüchtling**e**", "Flüchtling**en**" depending on grammatical context. For topic analysis, however, it is only important that she writes about the *issue* of refugees. Researchers generally use one of two techniques for *term unification*: stemming, and lemmatization. The simpler approach is stemming, which converts the inflected form of a word into its "stem" (Welbers et al. 2017). As Lucas et al. write:

[34] The earlier step of punctuation removal can either be done by removing for example a full stop completely or replacing it with a blank. The German abbreviation „m.E.“ then either becomes „mE“ or „m E „ – in both cases, this pre-processing step will remove it.

> *"Stemming is useful in any language that changes the end of the word in order to convey a tense or number […]. Since tense and number are generally not indicative of the topic of the text, combining these terms can be useful for reducing the dimension of the input" (2015:257-258).*

However, stemming will strip each suffix that contains the inflexion or derivation, meaning it will often leave non-lexical entries or even create the same stem from two similar, yet different words. In addition, stemming becomes more complex in languages like German, that are morphologically more complex than English. The plural form might change the stem (e.g. singular: "Maus", plural "Mäuse"), or the same letters might in one word be part of the stem, while these letters are part of the suffix in others (Caumanns 1999). Therefore, especially in the German case, many researchers prefer lemmatization to stemming, albeit its greater complexity, as it does require a lexicon instead of an algorithm. Instead of a chopped-off and hard to interpret stem, lemmatization thus converts every inflexion to its lexical form, or lemma. I used the R-package textstem (Rinker 2018) in combination with a comprehensive list of 358,476 German token-lemma pairs (Měchura 2018) to lemmatize the corpus. This dictionary was also converted to lower case before lemmatizing the corpus. However, it must be said that no automated approach is perfect and minor inaccuracies must be accepted when opting for such an approach. For example, humans will usually deduce from context whether the German word "linken" reduces to the lemma "links", when used in context of political leaning, or whether it is already a lemma when meaning 'to betray' in German. In the context of this study, I nonetheless believe that the benefits of being able to process large quantities of text with an automated approach outweigh these minor deficiencies. *Tenthly*, relative pruning was applied. This technique removes both words that are very frequent across documents, i.e. appear in more than 99 per cent of all documents, or are very specific to one document, i.e. appear in less than 0.5 per cent of all documents. As the logic of topic models is based on the co-occurrence of words across documents, neither too frequent nor too infrequent words are useful to detect topics and thus add little information to the model (Maier et al. 2018; Reber 2018). The final corpus used for topic modeling thus contains 55,297 documents with 1,537 unique terms appearing 1,332,205 times in the posts and comments from 181 AAS-groups[35]. Each document contains the preprocessed text, a variable containing the AAS-group's label, the timestamp in the form of the elapsed days since the first observation (range [0-1700]), and a permanent ID that can help trace a processed document back to the raw data. With these metadata included, I can thus firstly explore the topics that emerge in discussion of AAS-groups and secondly test, whether some topics are more prevalent among some groups or during certain times.

However, one key concern in topic models is determining the adequate number of topics, *k*. It needs to be said, that there is no 'correct' value for the parameter k, or, as Maier et al. point out *"there is no statistical standard procedure to guide this selection; thus, this remains one of the most complicated tasks in the application of LDA topic modeling"* (2018:97). While a high number of k might be advantageous in terms of model fit, it might be difficult to interpret as the topics might be very specific. A number too low however might produce topics that are too broad and collapse different issues into the same category. Empirical measures to aid the selection of k

[35] After application of the various preprocessing steps, four groups were left without a document, as not enough content was produced by them.

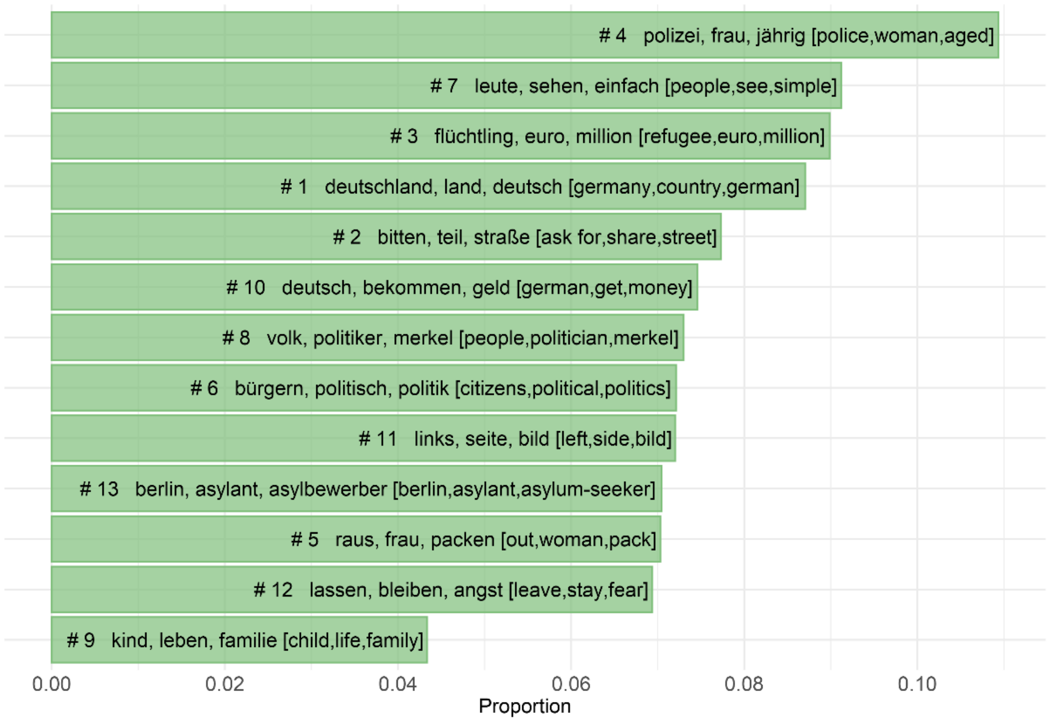
are being developed, and some of them are implemented in the stm-package (Roberts et al. 2016), like held out likelihood, residual analysis, semantic coherence and exclusivity. Despite these measures, researchers widely agree that the selection of k is first and foremost a substantial decision to be taken by the researcher based on the qualitative interpretation of results (Grimmer and Stewart 2013; Lucas et al. 2015; Maier et al. 2018). In other words, the correct number of k is different in every case and depends on the expectation a researcher has towards her data and the interpretability of the results. The standard practice in topic modelling is thus to run different models for a range of k and choose the resulting model that is most informative to the researcher. For example, in a study of Islamic fatwas, Lucas et al. (2015) ran models with 5, 10, and 15 topics, while Geese (2019) found 13 topics to be a good fit to study parliamentary speeches on immigration in Germany, while Stier et al. (2017) ran models with both 50 and 100 topics to classify the Facebook activities of German parties and right-wing populists. In my case, that is already very narrow in the sense that all groups explicitly focus on the issue of AAS-activity, it makes more sense to explore topical ranges similar to the first two studies mentioned. Therefore, I ran nineteen models ranging from two to twenty topics. The results for the empirical selection criteria described above are shown in Figure A.4 of the appendix. Both empirically and substantially, k=13 topics proved to be a good fit. Given the characteristics of the corpus discussed above, I believe this is a sensible and robust choice, based on my own evaluation of the alternative models. Many of the themes we will discuss in the next section also appeared in models with fewer or more topics. In general, when opting for a higher k-value, topics tend to become more localized, meaning we are likely to find more topics that deal with specific regional topics, and are likely dominated by few groups. A smaller number of topics generally led to more conflation and less granularity, making interpretation less clear-cut. Therefore, the following discussion is thus based on the result of a structural topic model with 13 topics, and with the document-level metavariables of AAS-group and day allowed to explain topic prevalence.

Results I

I will report results in two-steps: Firstly, as an exploration of the topics identified with the words (and in some cases examples of documents) that describe each topic best, along with the overall distribution of topics over the corpus. This will serve to illustrate what issues are debated among AAS-groups and which of them are more dominant or more marginal. Secondly, the temporal variation of topic prevalence will be explored and contextualized with the already known variation in AAS-activities and external events debated in a prior chapter.

Figure IV.10 gives a first overview of the model's results. It shows the proportionality of each topic in the corpus on the x-axis, along with the highest overall probability words and the topic number for each topic (i.e. the results of the term-topic matrix β).

Figure IV.10 Topic proportions, topic number and highest probability words per topic in the corpus



We can see that in general, proportions are almost equally distributed across topics. As we have 13 topics and proportions add up to 1, an entirely equal distribution would mean about 0.076 for each topic. Except for the topics 4 and 9, that are over-, respectively underrepresented in the corpus, the values for most topics range between .07 and .09. This means that we can already identify at least one topic that is more prevalent than others, yet not by a large margin. Table IV.3 aids a deeper understanding of the topics by printing out not the highest probability words for each topic, but instead the twelve words with highest FREX-score (Airoldi and Bischof 2016), that is "*the weighted harmonic mean of the word's rank in terms of exclusivity and frequency"* (Roberts et al. 2016:12). In other words, while some terms might be very frequent and thus have a high probability of appearing in many topics, the FREX-metric allows to understand topics in the terms that are both frequent *and* exclusive to a topic. Thus, they are neither too broad nor too specific, enabling a better comparison of topics than the probability score without being too narrow.

Table IV.3 Top-twelve FREX words in each topic

Topic Number and Label	Top-Twelve FREX words
#1 Islamic (terrorist) threat	europa, islam, muslim, türkei, islamisch, terrorist, europäisch, terror, frankreich, muslimisch, ungarn, moslem
#2 collective protest	demo, pegida, friedlich, dresden, teil, veranstaltung, freital, demonstration, protest, antifa, aktion, video
#3 economic costs	prozent, million, illegal, behörde, asyl, fordern, euro, flüchtling, steigen, milliarde, antrag, bundesregierung
#4 sexual violence	jährig, täter, verletzen, sexuell, polizist, übergreifen, mädchen, polizei, opfern, beamte, köln, mann
#5 insulting refugees	raus, packen, dreck, dreckspack, schwein, sofort, sowas, gesindel, abschieben, benehmen, knast, fressen
#6 local participation	bürgern, politisch, antwort, interesse, thema, bürger, frage, weiterhin, demokratie, entscheidung, somit, tatsache
#7 debating culture	nazi, leute, schön, denken, lesen, gerne, sage, böse, genau, egal, leider, naja
#8 insulting politicians	wählen, politiker, volk, wahl, grün, dumm, schande, blöd, regierung, hirn, verarschen, merkel
#9 language & integration	kind, eltern, lernen, familie, deutschen, fremd, integrieren, vater, leben, mutter, spiel, schüler
#10 disadvantaged Germans	geld, arbeit, bezahlen, obdachlos, bekommen, essen, steuer, rentner, kümmern, rente, kaufen, verdienen
#11 lügenpresse [lying press]	medium, artikel, facebook, links, bericht, presse, seite, hetzen, recht, lügenpresse, foto, interessant
#12 remigration	sichern, angst, überall, fahren, bleiben, lassen, sein, willkommen, heimat, fühlen, voll, hand
#13 asylum shelters	unterbringen, landkreis, gebäude, unterbringung, turnhalle, bezirk, asylheim, containerdorf, berliner, anwohner, unterkunft, hellersdorf

We can for example see that the most prevalent topic, number four, seems to discuss sexual violence against girls, as the terms “verletzen” [“to hurt”], “sexuell” [“sexual”], "übergreifen" ["to assault"], and "mädchen" ["girl"] illustrate. Topic nine, that was found to be least prevalent in terms of proportionality, seems to discuss the problem of integration of children ["kind"] to German schools and the role of families ["familie"] within it, as the terms "mutter" ["mother"], "vater" ["father"], and "schüler" ["pupil"], "lernen" ["to learn"], "fremd" ["foreign"], and "integration" express. To inspect results more systematically, the following pages will briefly discuss each of the topic's top terms and documents in an English translation and conclude with a shortened labeling of the topic, which is a common procedure in topic model interpretation.

Topic one seems to discuss the issue of Islam (not) belonging to Europe, as terms "europa" / "europäisch" ["Europe" / "European"], "islam", and "muslim" / "muslimisch" / "moslem" ["Muslim"] express. Islam seems to be strongly connected to terrorism, as the use of "terror" and "terrorist" imply. Further, the mentioning of France ["Frankreich"] might be in reference to the terrorist attacks in January and November 2015, in which IS-terrorists killed more than a hundred civilians in the French capital. For a better understanding of how these terms and concepts are interrelated, we can look at the documents with the highest document-topic (matrix θ) probability. Note that these are different from documents with an average probability for a certain topic and clearly do not represent the average document in the corpus – instead, as probabilities are unevenly distributed (see Appendix Figure A.5), only few of these documents as exist, as they are very *specific* to a given topic. In another words, such documents mostly contain words that are very distinct to a given topic and only contain few other words. Hence, they are ideal for the purpose of distinguishing topics from one another by describing what is specific to each one. Through the permanent identifier applied to each document before preprocessing, we can trace back each document of the corpus to the original text as it appeared on Facebook. In the case of topic one, the original text (slightly formatted and translated) of the highest probability document (p =.76) read:

> *"King of Jordan: Turkey sends terrorists to Europe. The Jordan king Abdullah accused Turkey of sending Terrorists to Europe. This is part of the Turkish president Erdogan's policy."*[36]

The second-highest probability document (p =.69) read (in excepts):

> *"In 2020 at the latest, there will be widespread persecution of Christians by Muslims all over Europe. The tolerant of today will be the persecuted, tortured, and killed of tomorrow. Bishop: Islam will take over power in Europe. Isa Gürbüz, Syrian-Orthodox head of church in Switzerland, warns of Islam. Muslims in Europe will proliferate and then begin with the persecution of Non-Muslims."*[37]

These documents are revealing of a view of Islam, that is centered on fears of terrorism and of an exchange of the European population with Muslims[38] that will eventually eradicate all non-Muslims. We can clearly see that the ideas propagated in this debate are dangerously close to conspiracy theories of the political right-wing and their racist

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[36] Original German: "König von Jordanien: Türkei schickt Terroristen nach Europa. Der jordanische König Abdullah hat die Türkei beschuldigt, Terroristen nach Europa zu schicken. Dies sei Teil der Politik des türkischen Präsidenten Erdogan."

[37] Original German: "Spätestens 2020 wird es flächendeckend die Christenverfolgung durch Muslime in ganz Europa geben. Die Toleranten von heute werden die Verfolgten, Gefolterten und Getöteten von Morgen sein. Bischof: Der Islam wird in Europa die Macht übernehmen. Isa Gürbüz, das syrisch-orthodoxe Kirchenoberhaupt in der Schweiz, warnt vor dem Islam. Die Muslime würden sich in Europa stark vermehren und dann mit der Verfolgung von Nicht-Muslimen beginnen."

[38] A term frequently employed by German right-wing conspiracy theorists in this context is "Umvolkung", which very roughly translates to "replacement of population".

idea of an ethno-nationalist culture war. For short, I labelled this topic *"Islamic (terrorist) threat"*.

Topic Two is one of the most important in terms of studying collective action. Among the top words in terms of probability are "bitte" and "danke", polite German words meaning "please" and "thank you", as well as "teilen" ["to share"], "demos" [short for "demonstrations"], "protest", and "straße" ["street"]. Among the FREX terms are also "friedlich" ["peaceful"], "veranstaltung" ["event"], "pegida", and "Dresden". This reveals two things: On the one hand, a proximity to and mobilization for the protests organized by PEGIDA in Dresden, and on the other hand, an understanding of the self as peaceful and polite[39]. The top-two documents related to this topic (p =.83 and .80) are both mobilization calls for demonstrations, one in the South-West of Germany and the other in Saxony. One of them reads (in excerpts):

> *"The biggest evening walk in the history of the Erzgebirge will take place this Saturday, 23.01.2016. It is time for 'MUT ZUR WAHRHEIT' (daring the truth). The 27th of November has shown that unity and collaboration pay off. Again, all citizen initiatives from Erzgebirge have united. Movements from Vogtland, Thuringia and Brandenburg will support us. […] Together for freedom, tradition, and 'heimat' (sense of home). Municipalities unite to one force."*[40]

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[39] This becomes even more apparent when compared to the insulting terminology used in other topics.
[40] Original German: Der größte Abendspaziergang in der Geschichte unseres Erzgebirges wird an diesem Samstag den 23.01.2016 stattfinden. Es ist Zeit für den "MUT ZUR WAHRHEIT" Der 27 November hat gezeigt, das Zusammenhalt und Zusammenarbeit sich auszahlt. Auch dieses mal haben sich alle Bürgerinitiativen aus dem Erzgebirge zusammengeschlossen. Bewegungen aus dem Vogtland, Thüringen und Brandenburg werden uns unterstützen. […] Gemeinsam für Freiheit, Tradition und Heimat. Gemeinden vereinigt euch zu einer Kraft."

The messages typical of this topic usually revolve around protest events, inviting citizens to join and calling for unity and solidarity among protesters and protest groups. Therefore, I labelled this topic *"collective protest"*.

Topic three discusses the rising economic costs of asylum for the German state, as the usage of "million", "milliarde" ["billion"], "euro", "prozent" ["percent"], "fordern" ["to demand"], "steigen" ["to raise"] indicates. This is discussed in conjunction with the legal process of seeking asylum, as the terms "antrag" ["application"], "behörde" ["authority"], "bundesregierung" ["federal government"], and "illegal" show.

The highest probability document for this topic (p =.80) is the discussion around a post that reports statistics on the percentage of population who receive welfare benefits (colloquially called "Hartz IV") in selected German cities. The post explicitly separates the numbers by German and non-German recipients, trying to illustrate the high expenditures of the German welfare system on non-German citizens. The second and third highest probabilities (both p =.75) stem from documents that also discuss the numbers and percentages of asylum-seekers who receive money from welfare funds, finding them higher than the population average. These documents also report numbers for asylum-seekers whose applications have been rejected but who still receive monetary support. The general tone of these posts is rather neutral, quoting official statistics or newspaper reports as credible sources. The comments to these posts however reveal the users' evaluations, that often delegitimize the German government and show a crude understanding of (international) law regulating asylum, as this quote exemplifies:

> *"Since the German Volk (people) at no point in time wanted or asked for immigration, all of them (asylum seekers) are illegal to me."*[41]

For short, I labelled this topic "*economic costs*".

Topic four has briefly been discussed above. Terms referring to sexual violence against women are typical for this topic, as is the debate of the role of the German police, as the terms "polizist" ["policeman"], "polizei" ["police"], and "beamter" ["officer"] illustrate. Also, the age of either the women or the perpetrators seems to be central, as xx- "jährig" ["aged xx"] is the highest rated FREX-term for this topic. A look at the top three documents (p =.95, .94, and .93) shows that they are posts in the style of short news reports or police communiques, listing incidents of rape and sexual violence perpetrated by foreigners against German women. In this style of seemingly neutral news reports, it is common to report both the age of the victim and the perpetrator. Although, a closer look at these documents shows that more often, the victim's age is reported, as they are mostly young girls under the age of twenty. The rationale behind these posts is probably to spark sympathy due to the victim's young age and portray immigrants as sexual predators. Therefore, I labelled this topic *"sexual violence"*.

Topic five is harder to interpret, as the key terms are almost exclusively insulting and swearwords, like "dreck" ["dirt"], "pack", "dreckspack" ["dirty pack"], "gesindel" ["ragtag"]. The words "raus" ["out"] and "abschieben" ["to deport"], "sofort" ["now"] show that the call to deport asylum-seekers is pronounced with violent urgency. The fact that no single document has a probability of more than .65 to belong to this topic,

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[41] Original German: „Da das deutsche Volk zu keinem Zeitpunkt die Zuwanderung gewollt oder gefordert hatte, sind sie für mich alle illegal."

shows that (in comparison to some other topic) these demands are rarely the only content of a document, but rather seem to be a reaction within comments than the main content of a post. The four highest probability documents are all short links to reports about (sexual) crimes committed by asylum-seekers, that are followed by lengthy and ugly insults in the comments section, calling for incarceration or castration of all refugees. For short, I labelled this topic "*insulting refugees*".

Topic six seems to discuss the participation of citizens in political decision-making regarding asylum – or, to be more precise, the lack thereof. Among the key terms for this topic are "bürger" ["citizen"], "politisch" ["political"], "demokratie" ["democracy"], in combination with "interesse" ["interest"], "frage" ["question"], and "antwort" ["answer"]. All of these words are typical of a debate on democratic processes, in which citizens voice their questions and concerns to elected representatives. A look at the three highest probability documents for this topic (p =.57, .56, and .55) reveals that the debates therein revolve around democratic processes like municipal elections and the fear of a leftist mayor in one town, the demand for more transparency in the sessions of the municipal parliament of another town through live streams on the internet, or the squandering of money in another city's administration. An obvious commonality of these documents is the focus on regional politics. Thus, the concerns in these debates are not addressed to the federal government, but rather to local authorities. Therefore, I labelled this topic "*local participation*".

Topic seven is harder to interpret by just it's key terms. We can identify words that are negatively connoted like "böse" ["evil"] or "leider" ["unfortunately"], as well as positively connoted like "schön" ["beautiful"] or "gerne" ["gladly"], along with verbs like "denken" ["to think"], "sagen" ["to say"], or "lesen" ["to read"]. Striking is the top-term both in overall probability and FREX-metric, which is nazi. Earlier in this thesis I have briefly touched the debate of the discrepancy between the political self-positioning of AAS-groups and the nature of their beliefs and demands. This topic seems to capture this controversy, as it stresses the civil and peaceful culture of debate among AAS-groups in stark contrast to the leftish, uncivil mainstream. The three highest probability documents for this topic (p =.53, .50, and .48) exemplify this reasoning. In this logic, "nazi" becomes a mere rhetorical weapon used by leftists who do not want to see reality. AAS-groups, however, can impossibly be nazis, as one commentator explains:

> *"I have to say something. I read nazi etc. a lot. But none of us can be a nazi, because if anyone of us should be a nazi, he'd have to be more than 80 years old. This means if anything people are nationalists, but not nazis."*[42]

Another comment laments the lack of a civic discussion culture of the left – something AAS-groups cannot be accused of:

> *"I was insulted as an npd [National Democratic Party, see chapter III] bratze [ugly woman] on your page and then the kommis [comments] were gone despite me not having attacked anyone and having soberly expressed my opinion […]"*[43]

The failure of the political opposition to see reality clearly is exemplified in this quote:

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[42] Original German: „Also ich muss jetzt auch mal was sagen ich lese so oft Nazis usw. Dabei kann keiner von uns ein Nazi sein denn wenn einer von uns ein Nazi seien sollte müsste er über 80jahre alt sein. Das heißt die Leute sind wenn überhaupt Nationalisten und keine Nazis."

[43] Original German: "als npd bratze wurde ich beschimpft auf eurer Seite und dann waren die kommis weg obwohl ich nimanden angegriffen habe und sachlich meine Meinung geschrieben habe […]"

"With this, the other group would admit that not everything is as beautiful as they want to tell us. That, they cannot acknowledge."[44]

The mainline of reasoning within this topic is thus one that accredits a civil and sober culture of debate to AAS-groups, while leftist loudmouths are the ones who are unable and unwilling to have a debate based on facts but instead try to discredit concerned citizens as "nazis". Therefore, I labelled this topic "*debating culture*".

Topic eight is in stark contrast to the claim of civility, as it contains a wide array of defamations of politicians, as the terms "dumm" ["stupid"], "blöd" ["stupid"], "verarschen" ["to shit someone"], or "schande" ["disgrace"] express. The reasoning of this topic is that politicians ["politiker"] and the government ["regierung"] of chancellor Merkel or the Green party ["grün"] betrayed the German people ["volk"]. Politicians are generally seen as not legitimized by the true will of the German people, as these comments to the election of German President[45] Frank Walter Steinmeier (the highest probability document, p =.66) show:

"A bunch of assholes, exploiters and nothing more, there is always money to raise parliamentary allowances, the stupid 'volk' will work for it."[46]

Especially the Green party, who took a liberal stance toward immigration and welcomed refugees, defending the right to asylum, is subject to ugly defamations in the documents of this topic. According to AAS-activists, Green politicians have nothing but "*shit in their brain*" and are "*always on drugs*". As these defamations

[44] Original German: "Da würde die andere Gruppe ja zugeben das nicht alles so schön ist wie sie uns erzählen wollen. Das können sie sich nicht eingestehen."
[45] In Germany, the President has little executive power, but rather representative functions. She is not elected directly by the people, but the "Bundesversammlung", which in turn consists of the federal parliament and representatives appointed by the German Länder.
[46] Original German: "Ein Haufen Arschlöcher, Ausbeuter und nicht mehr, für die Diäten Erhöhung ist immer Geld da, ja das bekloppte Volk arbeitet das schon wieder rein"

clearly outweigh any reasonable comments in my inspection of documents related to this topic, I labelled it "*insulting politicians*".

Topic nine has been briefly discussed above. It is the smallest topic in terms of proportion of the entire corpus, and its key terms indicate a discussion about the problems of integrating children whose parents do not speak German into German schools. The highest probability document (p =.57) starts by quoting a newspaper report that called for German schools to introduce Arabic language classes. For AAS-groups that would be an unthinkable betrayal of German identity, as one comment illustrates:

> *"We are German and speak German if they come here, they have to adapt and speak our language and not the other way 'round where would that lead, eh"*[47]

Thus, for AAS-groups, integration can only be a one-way process of assimilation and adaptation to a mainstream German culture (in German: "Leitkultur"). As learning the German language is crucial to this, I labelled the topic "*language & integration*".

Topic ten is similar to topic three, as it also debates economic aspects ("geld" ["money"], "bezahlen" ["to pay"]) and the costs of asylum. The focus, however, is slightly different, as the debate evolves more around the prioritization of government spending ("steuer" ["tax"]), that should go to homeless ["obdachlos"] or elderly people ["rentner"]. The three documents with the highest probability for this topic (p =.72 for all) are all discussions around the same original post, that is a text called "An alle Flüchtlingshelfer in Deutschland !!!!!!" ["To all supporters of refugees in Germany"], that originally appeared within German groups on the Russian Social Media Platform

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[47] Original German: "Wir sind deutsch und sprechen auch deutsch wenn die hier her kommen müssen die sich anpassen und unsere Sprache sprechen nicht anders Rum wo kommen wa denn da hin eh"

VK und was later spread across different groups. The text is lengthy and pathetic and describes the benefits that refugees receive in Germany and that were allegedly denied to German unemployed, homeless, and elderly. Some of the rhetoric questions of the text read as follows:

> *"Are you also the 'nice Granma' for German children? Do you collect food in shops for the poor Germans and give it to the homeless? Do you see to it that Germans have a roof over their head all year round? Do you pay for boarding houses and hotels so they can stay the night for free?"*[48]

The logic of this argument is basically "Germans First", meaning that where financial resources are scarce, Germans should be the prime recipients of both public welfare and neighborly solidarity, before any refugee or asylum seeker is helped. Therefore, I labelled this topic "*disadvantaged Germans*".

Topic eleven features a term well known in the populist dictionary: "lügenpresse" ["lying press"]. Other key terms for this topic include "medium" ["media"], "artikel" ["article"], presse ["press"], and "bericht" ["report"]. Thus, the topic seems to be critical of mainstream media, who, like the left political opposition ["links"] of topic seven, fail to acknowledge the reality about asylum-seekers but instead agitate ["hetzen"] against the concerned citizens in AAS-groups. The term "facebook" also appears in this topic, primarily in the context of a fear of regulation and policing of the platform, that is seen as an undemocratic censorship of AAS-groups. The document with the highest probability for this topic (p =.55) starts with a

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[48] Original German: "Seid ihr auch die "liebe Oma" für deutsche Kinder? Sammelt ihr in Geschäften Lebenmittel ein, für die armen Deutschen, um sie dann an Obdachlose zu verteilen? Kümmert ihr euch darum, dass die Deutschen das ganze Jahr über ein Dach über dem Kopf haben? Zahlt ihr den armen Deutschen Pensionen und Hotels, damit sie da kostenfrei übernachten können?"

post on the regulation of Facebook that reads *"Freedom of speech in danger. Constitution Article 5. Dictatorship on the rise."*[49]

We can thus identify a reasoning already familiar from other topics. The own actions are covered by freedom of speech, while any oppositional forces are oppressors of truth. The self is always depicted as the calm voice of reason while the *other* is loud, crazy, aggressive, and dangerous. The documents of this topic draw a picture of the mass media as being unable or unwilling to tell the truth, instead supporting the acting government in their betrayal of the German people. I therefore labelled this topic "*lügenpresse*".

Topic twelve does not have documents that belong to this topic as clearly as for other topics. The highest document-topic probabilities are thus lower than in other cases, with alpha values of .32, .30, and .28 for the top documents. It might thus be a topic, that is not as clear-cut as others, but instead represents a theme underlying many other debates. The terms seem to hint at the perceived threat by immigrants, with "fühlen" ["to feel"] or "angst" ["fear"] among the key terms. While "fahren" ["to drive"], "sein" ["to be"], "willkommen" ["welcome"], and "heimat" ["sense of home"], indicate a debate about the coming and going of people, the documents show that the main debate is one about "remigration", calling for the swift return of immigrants to their "homes" and expressing wishes, that this can be handled quickly. "Heimat" in this topic is not only the place migrants have to go back to, but the place Germans have to defend. Some of the documents are literal calls to arms, expressing the hope that Germans, who are at the "frontline" of migration will eventually start to

[49] Original German: "Meinungsfreiheit in Gefahr GG Artikel 5 Diktatur im Vormarsch."

fight back. Overall however, the dominating theme in these documents seems to be the (more or less violently) expressed wish for immigrants to “go home”. Therefore, I labelled this topic “*remigration*”.

Topic thirteen is a topic dominated clearly by the debate around the actual shelters or houses for refugees and asylum-seekers. The terms “unterbringung”/”unterkunft”/”unterbringen” [“accommodation”/”to accommodate”], “asylheim” [“asylum-shelter”], “gebäude” [“building”], “containerdorf” [“container village”], “turnhalle” [“gymnasium”] illustrate that the discussion revolves around the actual physical edifices that make migration tangible for many local residents [“anwohner”]. In addition, the key terms seem localized around the German capital Berlin [“berliner”], whose districts are called “bezirke”, one of which is “hellersdorf”. It is striking that no adjectives appear among the highest probability or FREX terms, meaning that evaluations of local situations are not typical for this topic, which is instead focused on a neutral reporting on the actual or planned sites of asylum shelters. The three highest probability documents (p =.85, .84, .83) are all plain reports about the location of asylum shelters in two Berlin districts and one small South-German town. Therefore, I labelled this topic “*asylum shelters*.”

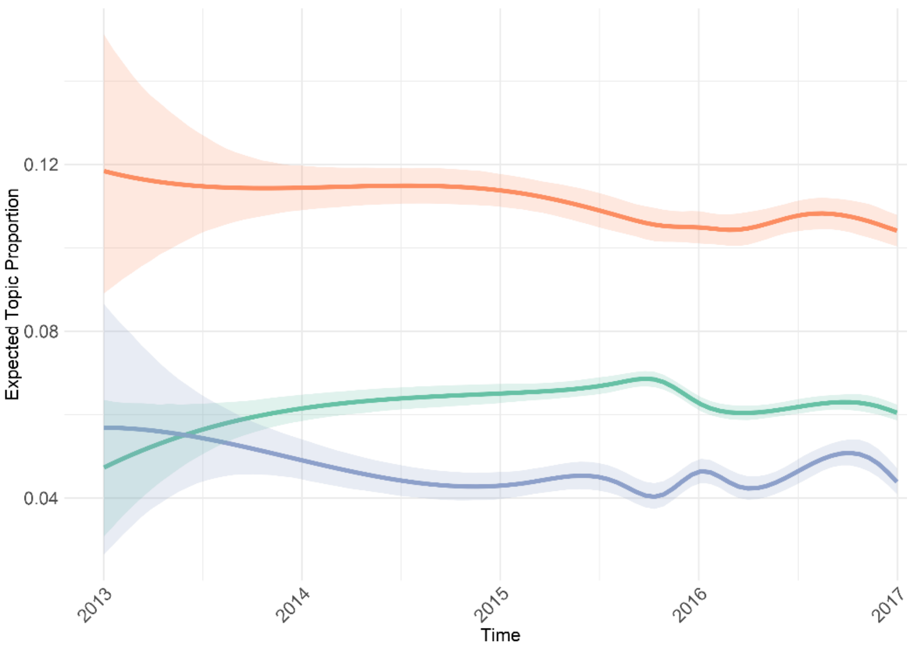
After having explored and labelled each topic separately, I will continue with an evaluation of the overall picture this content leaves us with. The research questions posed at the beginning of this chapter were: *What are the topics that members of AAS-groups discuss and how are these topics discussed? Can collective identities of ‘us’ and ‘them’ be identified in these debates and how are these collectives portrayed? Can temporal patterns of topic prevalence be identified that correspond to those identified in the overall activity of AAS-groups? Are some AAS-groups closer in terms of a* *homogeneity of topics than others?* In summary, this exploration of topics leaves us with a couple of answers to these questions. As a first conclusion, the topic model was able to provide thirteen clear-cut and interpretable topics. It could be shown that members of AAS-groups use the Facebook platform to almost exclusively discuss various aspects of migration and asylum, and do not stray from the overall theme. The narratives produced throughout these debates are clearly aimed at fostering a collective sense of "us" and "them". Us, that is the one part of the German "Volk", who have realized the threats of mass-immigration and the failures of politicians to regulate it. Members of AAS-groups perceive the self as peaceful and reasonable, whereas the political opposition is generally depicted as loud, hysterical, and aggressive. Thus "nazi" becomes a political term employed by the opposition to badmouth concerned citizens and silence any voice of reason. In turn, the collective "them" consists of different actors, that are all equally wrong: On the one hand, the mentioned leftist mainstream of society in their misguided "welcoming culture". On the other hand, the leftist-green politicians who "imported" migrants seem to conspire with the "lying press" that fails to tell the truth about migrants (the third category of "them") and the problems that they bring. These problems are as follows: Refugees cost money, that would be better spent on Germans. Thus, politicians fail to allocate resources properly. Refugees are unable and unwilling to assimilate properly into German culture by learning German. Refugees bring Islamist terrorism to Germany. Refugees bring sexual violence to Germany. The cognitive dissonance of propagating clearly right-wing ideology while at the same time claiming to represent the political center of society can be observed in many instances of recent extreme right phenomena, from PEGIDA to the Identitarian Movement (Knüpfer et al. 2019). Therefore, we can conclude that SNS are employed in several mechanisms of collective action coordination. The debates among AAS-groups clearly foster a sense of collective “we” in sharp demarcation from a collective “them”. In addition, topic thirteen shows that SNS are used to collect and disseminate factual information about the central issue of asylum-shelters, while topic two shows that SNS are used to coordinate and mobilize for street protest. Again, it needs to be stressed that the perspective on SNS and collective action taken in this thesis is not one that tries to calculate effects or establish causality. Instead, it is focused on *how* different groups use SNS to coordinate collective action. Therefore, in the next section I will explore the “structural” part of structural topic models and explore the temporal patterns of topic prevalence.

Results II

The exploration of topic content in the previous section provides some guidance to the investigation of temporal variation. This means that some of the topics can be expected to change little, as they debate more or less stable issues like the “lying press”, or “remigration”. Others, however, like “sexual violence” or “Islamic threat” can be expected to gain more attention through external shocks like the mentioned events in Paris, Berlin, and Cologne. Starting with the topics “remigration” (green), “lügenpresse” (orange), and “language & integration” (blue) in Figure IV.11, I will exemplify these dynamics using the expected mean topic proportionality for selected topics over time. To do so, I used the “estimateEffects” functions in the R-package “stm” (Roberts et al. 2016). The function performs a regression with topic proportions as the dependent variable, with the document metadata as covariates. The Figures in this section thus show the smoothed effect of the time-variable on topic proportionality in our model. The timeframe is limited to the years 2013-2016, as there was not always enough data before and after for every topic, leading to high uncertainty in the estimates of the model. From our analyses in chapter IV-I, we know that activity among AAS-groups was generally sparse prior to 2014, meaning that few documents in our corpus predate this, which is reflected in the wide confidence intervals of Figure IV.11 and following Figures.

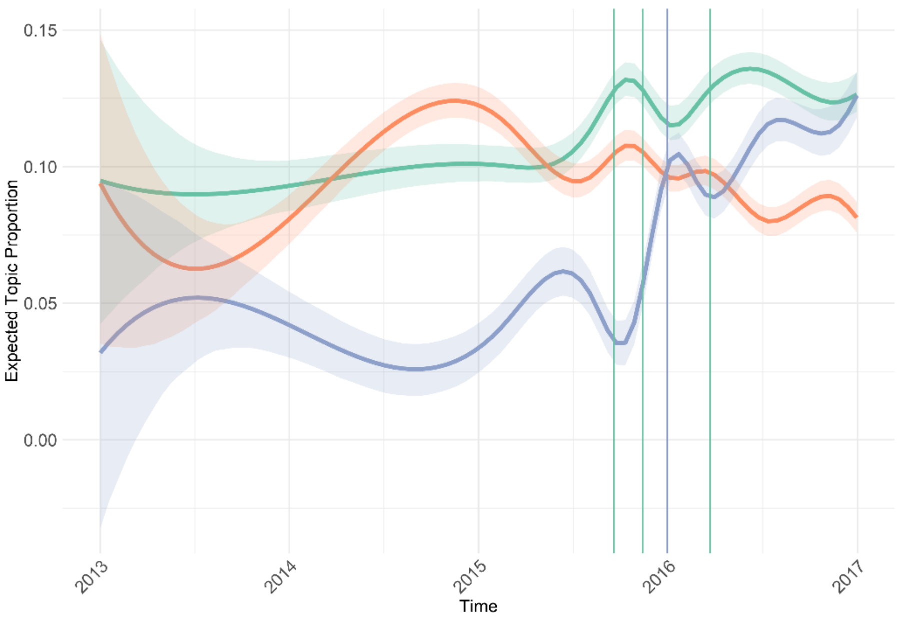
As the figure shows, there is little change in the expected prevalence of these three topics. The wish for asylum-seekers and refugees to leave Germany, the inability of non-Germans to adapt, and the critique of the lying media all remain more or less stable over time. The overall level however is different: A critique of the media is clearly more prevalent throughout the observed period than the other two topics.

Figure IV.11 Mean expected topic proportion for remigration (green), lügenpresse (orange), and language & integration (blue) with .95 confidence interval.



Other topics, however, are not as stable, as Figure IV.12 shows. We find the topic of "Islamic threat" (green) to be constantly high, and even shifting upwards in the fall of 2015. This may be driven by the overall rise of terrorism on European soil, and especially the events in Berlin in September 2015, when an Islamist attacked a police officer with a knife, in Paris in November 2015, when a coordinated attack on multiple targets killed more than a hundred people, or the suicide bombing at Brussel's airport and Metro in March 2016 (green vertical lines in Figure IV.12). The fact that "France" was among the FREX-terms of this topics, supports the assumption that it was real life events that lead to an upward shift in the topic's proportionality. This is even more apparent for the topic of "sexual violence" (blue), that did not seem to be among the prime concerns of AAS-groups prior to 2016. The mean expected proportionality rarely exceeds .05 before the already debated New Year's Eve events in Cologne (see chapter III), but these clearly mark an upward shift for this topic (blue vertical line in Figure IV.12). This shows that in the depiction of the collective "other", AAS-groups were not fixed from the beginning on, but remained ready to adapt and reframe their agenda, depending on external events that might benefit their cause. Indeed, given its low initial proportion, the 'career' of this topic to become the most prevalent in the aggregated corpus is even more remarkable. This supports the conclusion of the key role of external events and especially the New Year's Eve in Cologne in both shifting up overall activity and offering a narrative of the collective enemy. The topic "collective protest" (orange) however, peaks earlier and achieves the highest proportions in the fall of 2014. This is the same time, the anti-Islamic PEGIDA group made headlines by mobilizing thousands of people to their protest marches in the Saxonian capital of Dresden.

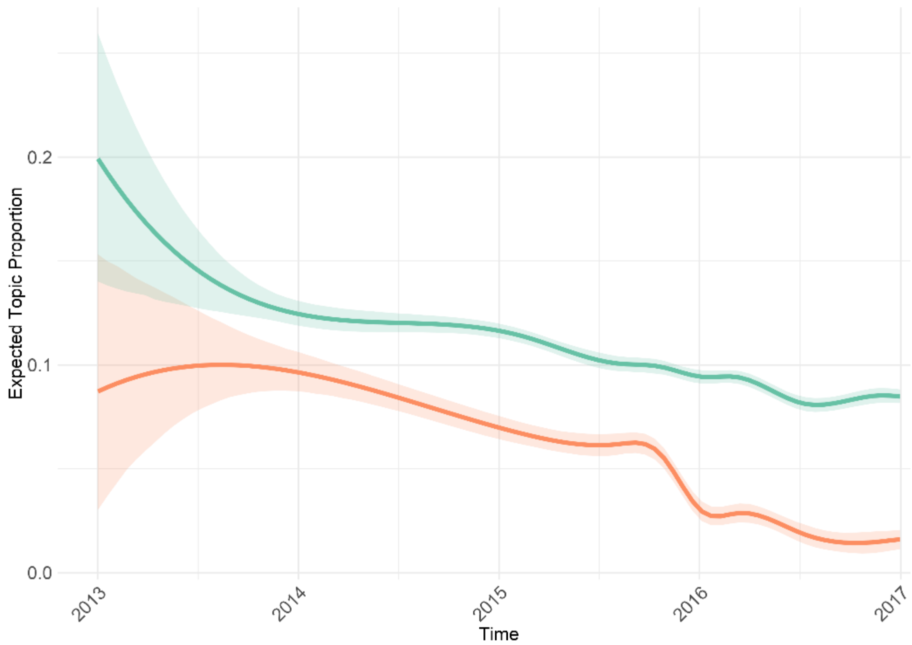
Figure IV.12 Mean expected topic proportion for Islamic threat (green), collective protest (orange), and sexual violence (blue) with .95 confidence interval.



The second, smaller peak of this chart in the fall of 2015 corresponds to the highest overall activity in terms of AAS-demonstrations, that I have illustrated in Figure IV.6, earlier in this thesis. After that, the topic's expected proportion drops slightly. This is however not equivalent to it loosing importance in absolute terms: As we have seen in Figure IV.8, overall AAS-activity remains on a high level throughout 2016. Thus, a decrease in relative importance as shown here means that other topics concentrate more of the overall attention, while the total interest in collective protest is not necessarily decreasing.

The last visualization of topic prevalence over time is Figure IV.13, showing the expected topic proportionality of "local participation" (green) and "asylum shelters" (orange). We can see that throughout the first half of the observation period, the proportion of local participation exceeds .10, but the topic slightly loses relative importance over time. This may mean that in the beginning, local initiatives and direct citizen participation gained more relative attention, but over time were crowded out by more general and overarching issues or groups that focused less on local, but national initiative or more on the collective "them" than about own activities. An even greater relative decline over time can be observed in the topic asylum-shelters, that is almost reduced to zero during the course of 2016. We may speculate that the novelty of the construction of asylum-shelters that was the foundation of AAS-activity gradually lost its importance as external events like terrorist attacks and sexual violence proved a more stable and easier to feed narrative of threat and danger.

Figure IV.13 Mean expected topic proportion for local participation (green) and asylum shelters (orange) with .95 confidence interval.



Summing up, this brief inspection of the temporal variance of topic proportions illustrated some of the basic properties of the corpus. *Firstly*, while some topics remain more or less stable over time, others are more volatile in terms of proportionality. *Secondly*, this volatility seems to be strongly driven by external events that might open up new discursive opportunities to AAS-activists. *Thirdly*, the major shifts in topic prevalence go hand in hand with shifts in the overall activity of AAS-groups explored earlier.

Chapter Summary

In conclusion, this chapter has been able to provide a comprehensive overview of the topics that AAS-groups are concerned with and the dynamics that shape their debates. These served to answer most of the research questions from RQ-set II that asked which topics can be identified in debates of AAS-groups, how these topics are discussed, and what collective identities and temporal patterns exist in these debates. It could be shown that structural topic models allow for a meaningful analysis of textual data in this case, providing 13 interpretable topics. From the proportion of topics in the corpus, we could learn that sexual violence perpetrated by foreign men against German women is the top concern among AAS-activists. In addition, we learned that topic proportionality as a measure of importance of a topic is not always stable but seems to be influenced by external events like the incidents in Cologne in 2015/2016. Further, we could see that debates on social media serve to foster a common understanding of the collective 'us' and the (multiple) collective 'them', where the self is reasonable, calm, concerned, and able to see the truth - whereas politicians, media, and the leftist mainstream ("Gutmenschen") are portrayed as delusional or lying and foreigners are portrayed as sexually violent, terrorists, or unwilling to adapt to the values of German culture.

Since we are interested in the role of ICT for collective action processes, we could learn that, indeed, the affordances of the Facebook platform are utilized to create and reinforce common framing and collective identities. These are neither stable nor independent of outside factors, as the shifting topic proportionality in conjunction with external events revealed. Also, as chapter IV-i has shown, not all groups show the same activity and engagement in this regard, meaning that there is clearly no technological determinism, but groups make very different use of various technological affordances. This aspect will be deepened in the following chapters, that investigates how different groups make different use of the affordances of SNS and how these usages combine into different Modes of Coordination.

IV-iii Networks and Modes of Coordination

In this section, I will use the Facebook dataset on all 185 AAS-groups as well as the results from the structural topic model in the previous chapter to investigate patterns of interactions among AAS-groups from the relational perspective of an MoC framework. This way, this section will seek to answer the research questions presented as RQ-set III, which I repeat here:

> *How do AAS-groups use social media? What types of ties amongst AAS-groups can be identified and what networks evolve from these ties? How do the types of ties correspond to mechanisms of resource allocation and boundary definition among AAS-groups? How do they combine into different Modes of Coordination of collective action?*

As the analysis is guided by a theoretical framework that allows for a typology of Modes of Coordination of collective action based on the two dimensions of resource allocation and boundary definition, this chapter will be structured along these two dimensions. Each type of tie and the network resulting from it is discussed in terms of its role in either resource exchange or boundary definition, before combining both dimensions into the different MoC discussed in detail in chapter II.

As Diani has highlighted (2015, 2018), these mechanisms play out on different levels, meaning that processes related to fostering exchange and forging solidarity may be at work between individuals, between an individual and an organization, as well as between organizations. It is the latter that allows for a mapping of the interorganizational networks which will be discussed in terms of Modes of Coordination in this chapter. Again, I want to iterate the fact that organization is perceived in a wider (or partial) sense, as discussed in chapter II, allowing to include the informal groups that form within and through the activities on Facebook pages. Despite their informal character, we will see that these groups do possess agency in the sense of an "*autonomous decisional capacity*" (Diani 2015:17), for example in recognizing each other as distinct groups, as the mutual recognition network will illustrate. Also, the organizational trait of a distinct core *membership* for each group despite no formal criteria for membership will be empirically supported by an investigation of user activity patterns in the co-membership network. Therefore, the following analyses will treat AAS-groups as partial organizations and hence analyze the patterned activities and interactions of users and administrators within the MoC framework.

As such, we will delve deeper into the operationalization of the tie-based approach to Modes of Coordination that was laid out in chapter II. There, we have argued to focus our attention on the ties and networks that emerge from activists' usage of the affordances of Facebook. Thus, rather than opting for an inquiry of equivalent positions and roles, we seek to offer a theory-based understanding of how these affordances can be understood as supporting the mechanisms of resource exchange and boundary definition. To do so, we will investigate five different types of interorganizational ties and argue their relevance in light of our two conceptual dimensions. This is not to say that we have effectively covered each technological (or functional) affordance of the Facebook platform – or of other SNS for that matter – but instead opt to scrutinize our case based on the theoretical arguments laid out earlier. As such, we can offer a more nuanced understanding of digital ties and networks than many previous studies, that have relied on hyperlinks as opaque signifiers of all kinds of intergroup processes. None of the arguments made in this chapter are set in stone but should be understood as theoretically grounded suggestions to advance the debate on digital communication technology and collective action. Naturally, other researchers may emphasize different readings of the same data of focus on different technological aspects to operationalize ties. To me however, this chapter offers a close reading of the available data in light of our theoretical argument and the research questions that flow from it.

Resource Exchange

Mutual Recognition

The first network to be discussed here already includes a conceptual decision that may be contested. The mutual recognition network is based on the data of *page likes* among AAS-groups, as reported in chapter III. This captures what Simpson dubbed "*positive nomination"* (2015), as he argues that "*given their affective nature, liking amongst SMOs*[50] *may influence perceptions of closeness, making them apt for establishing (sub)movement boundaries around collective identity*" (Simpson 2015:49). Thus, the act of formally "*liking*" one another in the logic of an SNS is seen as *affective,* thus fostering boundaries and identities and as such closer to the "*deeper bonds of solidarity, mutual commitment, and emotional attachment*" (Diani 2015:14) that may be better grouped under *boundary definition* than *resource exchange*. This perspective may however underestimate the strategic aspect of *liking*, which signals to others who is perceived as part of a collectivity and who is not. As page likes construct hyperlinks between pages, collective action scholars often understand them as "*signs of belonging and potential means of alliance*" (Vicari 2014:92). I follow Shumate and Dewitt, who pointed out the conscious and strategic aspect of hyperlinking practices, stressing that "*the decision to link one organization with another is a strategic communicative choice*" (2008:407). As recommendations are visible in specific section called "pages liked by this page" to all visitors on a group's main page, these *likes* may channel visitors to other sites and thus serve as gateways to an exploration of the wider collectivity beyond any specific group. We may thus argue that *likes* direct users'

[50] i.e.: Social Movement Organizations

attention. This resonates well in perspective of *attention economy,* which posits attention as a scarce resource in an over-abundance of information (Goldhaber 1997; Simon 1971), especially in a hybrid media system (Zhang et al. 2018). We may thus very well argue that groups *liking* each other on SNS do not only signal their belonging to a collectivity, but also share the resource of their own members' attention with the expectation of reciprocity to receive attention from other groups' members. Therefore, while there are fair points to be made for seeing *likes* as a mechanism of boundary definition, I opt to treat it as a form of resource allocation in this thesis.

As described in chapter III, page *likes* are basically hyperlinks chosen by a page's administrator that appear in a specific section of the front page. As such, *likes* are recommendations, which administrators use to "*link their pages to other sites to which they feel somehow 'similar' and with which they share ideological traits*" (Tateo 2005). This is not be confused with individual *users' likes*, which have also been subject to academic debate (Brandtzaeg and Haugstveit 2014; Eranti and Lonkila 2015). Instead, a founder or appointed administrator of a group's page has the exclusive right to set page *likes*.

Table IV.4 Descriptive statistics on page likes

Page Likes	
Range	[0 – 259]
Zeros	88
Median	1
Mean	9.93
SD	27.26
Total	1,838

Empirically, Table IV.4 shows that the practice of page *likes* is by no means abundant, yet instead shows that groups seem to carefully choose whom they recommend and whom not. In fact, 88 groups do not use the function at all, thus leading to a median in page *likes* of only one. In total, I counted 1,838 of these *likes*, with an average of 9.9 and a maximum of 259. In addition, a qualitative exploration of each group's *likes* showed that the function is exclusively used to point to (perceived) similar pages or pages that might be aligned politically. While some link's targets were neutral, none of the *likes* pointed to political adversaries.

These data on acts of recognition not only *toward* groups outside of our population of AAS-groups, but also on these external groups' *own* recognition acts, allows to add empirical insights to our discussion on fields, subfields, and a field's population from chapter II. We know not only whom our 185 AAS-groups *liked* but also whom those 1,259 non-AAS-groups *liked*, which were initially *liked* by AAS-groups. This allows us to randomly select any 185 groups from this set of 1,444 groups that we have full information on, and compare the network of recognition among them to the network of recognition among only AAS-groups (which is going to be discussed in this chapter). In fact, out of 5,000 random samples, only 30, or .6 per cent, of the samples resulted in a network with a higher density than the network of only AAS-groups. In other words, we observe significantly more recognition among AAS-groups than among other members of the wider field. This supports our argument from chapter II that we may well speak of a subfield of AAS-groups that are clearly distinct in their relational patterns.

Thus, the following sections will discuss the network of (mutual) page likes among AAS-groups, interpreting these likes as a recommendation to distribute user attention and as acts of recognition among the members of a specific field's population.

Network Construction

To study page *likes* as a network of recognition among AAS-groups requires the transformation of the 185 edgelists introduced in chapter III into one adjacency matrix of the dimensions 185x185. The Sammlr application provides data on any outgoing page *like*, including links to pages that are not AAS-groups. As only relations among these groups are of interest here, any row of the edgelists that contained a non-AAS-group on the receiving side was deleted in a first step. In a second and third step, the lists were merged and transformed into an adjacency matrix with the both the number of rows and the number of columns equal to the number of AAS-groups. As recognition is not reciprocated by default, we speak of directed edges in this network, meaning the adjacency matrix is asymmetric. In other words, group A may like group B, but group B does not necessarily like group A back. In addition, the edges are unweighted, meaning that the strength of a relationship cannot be quantified in this network. In other words, group A can either like or not like group B, but there is no way to like one group *more* than any other. Because of these properties, we can speak of a *directed and unweighted* network of recognition.

In chapter III, I formulated a set of research questions to be answered by the analyses of the networked interactions among AAS-groups. These were intended to be very broad and general, asking among others: *How do AAS-groups use social media? What types of ties amongst AAS-groups can be identified and what networks evolve from these ties?* At this point, it becomes necessary to be more precise, make these overarching questions operationalizable, and thus lend structure to the following analyses. Therefore, we will ask firstly *what the overall structural properties of each of the networks are,* answered by graph-level measures such as density and centralization. Secondly, we ask *which key groups can be identified within each network,* answered by node-level measures such as degree and other centrality measures. And thirdly, we ask *what sub-groups or communities can be identified among AAS-groups within each network*, being answered by meso-level measures of community detection. Therefore, the analysis of the recognition network as well as any following analyses will be structured along the levels of *graph*, *nodes*, and *communities*.

Graph

One way to study how AAS-groups make use of the different affordances of SNS and mechanisms of coordinating collective action is to study the density of each network. Density measures the fraction of all possible ties in a network that are realized and as such informs us to what degree the nodes in a network are connected or not. In a directed network such as this, density is calculated with the formula $D = \frac{n}{Nx(N-1)}$ where *n* is the observed number of edges and *N* is the number of nodes in this network[51]. For the recognition network, density is .017, meaning that 1.7 per cent of all possible edges in this network are realized. If we were to leave out isolates, i.e. counting only edges between groups that do use recommendations at all, density rises to .024. Whether or not these figures are considered as high or low depends on each case and the numbers will become more meaningful, once we can compare them to the

[51] In the case of an undirected network, the denominator needs to be halved, as only one tie can exist between any pair of nodes.

other networks in the following sections[52]. As the network is directed, we may further look at the reciprocity of this graph, defined as the proportion of connections that are mutual. In this graph, reciprocity is .18, meaning that 18 per cent of all connections from any node A to any node B are also returned by node B. This indicates that when AAS-groups receive recommendations it seems far from automatic that they return this act. Therefore, a look at degree-measures on node level in the next sub-chapter will help to understand reciprocity in more detail. Apart from density, the overall structure of a network can be characterized as connected or disconnected. In SNA, a *connected* graph is one in which there is a *path,* between any pair of nodes, meaning that information or resources may in theory flow from any node A to any node B, no matter how many intermediaries are required (i.e. how long the path is). In this logic, a *component* is any *connected subgraph* of a *disconnected* graph, meaning that within a component, a path exists between any pair of nodes, while no paths exist across components (Wasserman and Faust 1994). Therefore, as soon as there are isolated nodes, that have no connection to any other node, a graph is disconnected. The number and size of components of this disconnected graph can provide important insights into the overall structure of the network. In the case of the recognition network, the graph is indeed disconnected, as 29 of the 185 AAS-groups both do not recommend another group and are not recommended by any other group. The remaining 156 groups are

[52] In general, density in a recognition network can be expected to decrease with network size, as it becomes more and more unlikely for many different actors to "know" everyone else. For a rough indication, it may be noted that the alliance networks Diani (2015) found among civil society actors in Glasgow (N=124) and Bristol (N=134) had densities of .023 and .015. Studies from the sector of right-wing internet networks report densities of .04 (N=77) for French extreme right websites (Froio 2018) and of .06 to .10 (N from 16 to 36) for different European right-wing online networks (Pavan and Caiani 2017). The observed value in our case can thus be considered to be well within the expected range for a network of such type and size.

connected in one big component, with an average path length of 3.67, meaning that on average, each shortest path between two nodes travels through almost three other nodes. In directed graphs we can further distinguish between *weak* and *strong* components. While weak components ignore the directionality of ties, a *strong* component is one in which information that originates from any node of the component will find a path to any other node of the component by "travelling" along the directions of the edges[53]. When applying this stricter criterion, three strong components of size > 1 remain, containing 53, four, and two of the network's nodes. The number of components and their size can be compared across networks and is one the measures that inform the researcher about a graph's cohesion (Borgatti et al. 2013). Analogous to an investigation of components, researchers can calculate a measure of *connectedness,* defined as the fraction of node-pairs that can reach each other through a path of any length (Borgatti et al. 2013; Krackhardt 1994), or its inverse *fragmentation* which is the fraction of nodes that cannot reach each other. All these measures may reflect external limitations as well as *strategic choices* by actors. Or, as Diani explains:

> *organizations may concentrate most of their resources on their own projects and devote a very limited amount of resources to collaborative initiatives, resulting in fairly sparse interorganizational networks. In other cases, resources invested in collaboration may be substantial and may lead to fairly dense networks* (2015:15).

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[53] The "recursively connected" component in which all ties are reciprocated would be a special case of the strong component (Wasserman and Faust 1994). As we already know that only 18 per cent of ties in this network are mutual, this cannot be the case here.

When applying the measure of connectedness to the recognition network, the score is .71, meaning that 71 per cent of all node pairs are able to reach each other, as they are in the same weak component. As mentioned above, the stricter criterion of a strong component leads to more fragmentation, letting the connectedness score drop to .08, as by this definition of reachability, much fewer connected pairs are possible. Again, this may be driven by a lack of reciprocity, meaning that recommending does not automatically lead to being recommended, but instead may indicate hierarchies in the network.

While Borgatti et al. (2013) would call the abovementioned measures indicators of cohesion, they also suggest characterizing whole networks using measures of *shape*. One of these measures that can reveal inequalities in the overall structure of a network, is *centralization.*

Centralization is a graph level measure that sums the difference of each node's centrality value to the maximum value and divides (i.e. normalizes) this sum by the theoretical maximum for this graph (Borgatti et al. 2013). For example, if an actor is central in terms of holding many connections to other actors, this measure of degree-centrality can be used to calculate the (degree-)centralization of a graph. For a perfect star as the most centralized graph possible, this value would be one. The more centralized a graph is, the more "power" do fewer groups in that network hold over more marginalized groups. For the recognition network, we can calculate a score of .12 for in-degree centralization, which measures the inequality in terms of popularity and a score of .29 for out-degree centralization, which measures the inequality in terms of outreach activity. While the node-level analysis in the next subchapter will reveal some insights on the distribution and relation of in- and outdegree between organizations, it might already be surprising at this point that the "receiving" end of attention is more evenly distributed than the "giving". It illustrates that some groups invest heavily in outreach-activity, likely in the search and expectation of recognition by other members of the field. Interestingly, Pavan and Caiani (2017) also found a consistent pattern of higher outdegree than indegree centralization in their comparison of six European online right-wing hyperlink networks, further supporting the assumptions that *page like* and *hyperlinks* function in a similar way. This also iterates the importance of the debate at the beginning of this section, namely the possibility of reading an act of recognition both in terms of resource exchange and in terms of boundary definition. While we will stick with the former for now, future research should address the ambiguity of recommendation-ties in digital environments more deeply.

Another measure that is called *transitivity* or *clustering coefficient* may reveal the degree to which nodes tend to cluttered together in tight knots, meaning this graph may be characterized by areas of very high density in some areas and low density in others (Borgatti et al. 2013). The measure is one of triadic closure, meaning it counts the number of any three nodes A, B, and C in which A and B as well as B and C are connected and calculates the fraction, for which A and C are also connected. Using this measure, we can calculate a transitivity score of .20 for the recognition network.

Table IV.5 sums up the above debate and presents these basic structural properties on graph-level. The interpretation will become clearer once we turn our attention to the other networks of resource exchange and boundary work and can add a comparative dimension. For now, I will continue the exploration of the recognition network on the micro-level of individual nodes to investigate hierarchies, inequalities, and mechanisms of reciprocity in more depth.

Table IV.5 Structural properties of the recognition network

Measure	Score
Edges	579
Density	.017
Reciprocity	.18
Fraction of Isolates	.16
Components (isolates excluded) weak/strong	1/3
Maximum Component Size weak/strong	156/53
Average Path Length	3.67
Connectedness weak/strong	.71/.08
Centralization (in-degree)	.12
Centralization (out-degree)	.29
Transitivity	.20

Nodes

In a directed network such as this, we can meaningfully distinguish between in- and outdegree of each node (i.e. group) in this network. Outdegree is the number of edges that originate from a node, i.e. the number of other AAS-groups that are nominated as *liked* by this group. In that sense, it might be interpreted as a measure of outreach or networking activity each group performs. Indegree, in turn, is the number of nominations each group receives from all other AAS-groups. In that sense, it might be interpreted as a measure of popularity. Or, as Ansell put it: "*High outdegree suggests that an organization is actively networking with other groups. High indegree indicates that an organization is prominent or perhaps powerful—other organizations seek its advice, resources, or influence*" (Ansell 2003:126).

Figure IV.14 Relationship between and frequency of in- and outdegree of each node (N=185) in the mutual recognition network

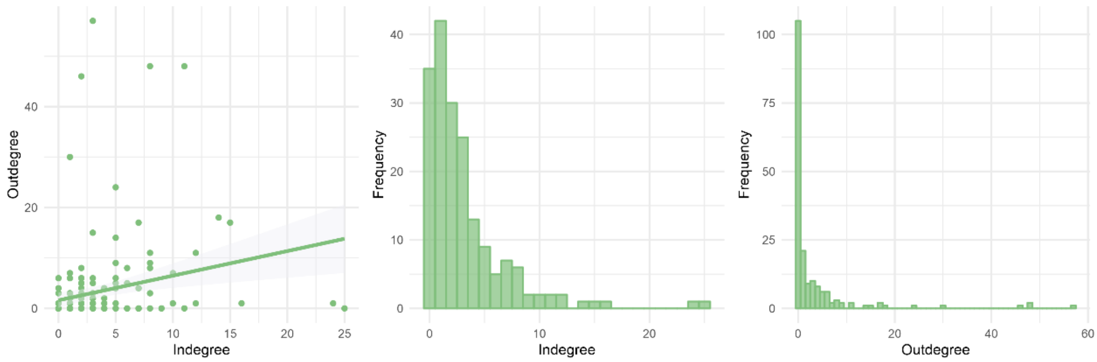

Figure IV.14 illustrates the both the distribution of in- and outdegree over nodes as well as the relationship between these two properties. Starting on the right of the figure, I will first discuss *outdegree* in this network. In Table IV.4 we have already learned that 88 of the 185 AAS-groups do not make use of Facebook's affordance to nominate other pages as "liked". When we restrict this to nominations only among AAS-groups, we can see that number rises to 105, i.e. the number of nodes with outdegree zero, as shown in the first bin of the histogram. In turn, this means that of the 97 AAS-groups, who did make public nominations, 80 did nominate another AAS-group, i.e. the number of nodes with outdegree above zero. From the relatively low median and mean scores of page *likes,* we could see that groups make careful use of this feature. Therefore, it is even more striking, that 93 per cent of groups who did make positive nominations did so to *at least one other* AAS-group. Hence at least among these groups we can assume an awareness of being part of the same collectivity. In addition, a look at this distribution reveals that there are a couple of groups, who make comparatively much use of the function, i.e. invest more in outreach activity. Namely the groups BW13, BW10, SN06, and SN33, two groups from Baden-Württemberg and two groups from Saxony, show outdegrees above 45, with a maximum of 57 for

BW13. As the scatterplot in Figure IV.14 shows, these are however not the same groups that receive much attention in terms of indegree. As the regression line shows, there is no strong linear relation between in- and outdegree, or between giving and receiving attention in this network – at least not for all groups. Instead, some of the highest nodes in terms of indegree have a relatively low or even zero outdegree, while some of the highest nodes in terms of outdegree, have relatively low indegree values. This may mean that reciprocity is not the key mechanism driving exchanges in this network, but instead recognition seems to be highly centered in very few popular nodes while others (unsuccessfully) seek this attention by reaching out to many other groups. In general, *indegree* seems to be distributed more evenly than outdegree. As the histogram shows, only 35 groups receive no nominations at all, while many groups receive nominations in a range of 1 to 12. The two groups that stand out with values of 24 and 25 are the Brandenburg group BB31 and the Germany-wide DE03. Interestingly, these groups also score very high in terms of receiving users' likes. This means that the assumption that indegree may be interpreted as a measure of popularity within a network can be corroborated with a measure of external popularity, i.e. user likes. Indeed, correlation tests show a strong and significant association[54] between external and internal popularity, while outreach activity (i.e. outdegree) and external popularity show only a weakly positive and not significant[55] association. In total, this exploration of in- and outdegree leaves us with three broad types of nodes in this network: groups with relatively equal scores for both popularity and outreach, groups

[54] Pearson's r: .56, Kendall's Tau .40 with both p values < .0001.
[55] Pearson's r: .05, Kendall's Tau .16, p not sig.

who reach out but receive little attention in return, and groups who are very popular without any outreach activity.

Communities

The study of subgroups in networks can be informed by different approaches. Some are based on the (structural or regular) equivalence of nodes, where nodes that are connected in similar patterns to alters form groups or blocks of nodes with similar positions or roles in a network. Other approaches are based on cohesion, like community detection algorithms that seek to identify subgroups which are characterized by "*many edges within communities and only a few between them*" (Clauset, Newman, and Moore 2004:1–2). Communities in a network are of interest, because "*the relative absence of ties across communities means that information will, more often than not, be trapped in the areas of higher internal density*" (González-Bailón and Wang 2016). Borgatti et al. (2013: 193) argue that a study of study cohesive subgroups[56], in social network analysis can reveal important insights, as

> *actors within cohesive subgroups tend to share norms and often have common goals and ideals. They can also exert considerable peer pressure on their members to conform to these norms. This means that group members frequently have similar outcomes with respect to adoption of innovation, behaviors and attitudes.*

On an interpersonal level, these subgroups or communities are often linked to a higher likelihood of information flow, as Himelboim et al. note:

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[56] Cohesive subgroups are often also called communities or clusters. The terms are used interchangeably.

Users create pathways for the flow of information when they create these connections. The resulting groups define the social boundaries of information flow; within these clusters, information flows freely, while across clusters information flow is restricted by the limited connectivity available across cluster (2017:3).

This is consistent with the findings of Lerman and Ghosh (2010) who empirically found that higher density can lead to a faster initial flow of information. In an interorganizational network, we can reasonably expect that when groups are densely linked by hyperlinks as "*signs of belonging and potential means of alliance*"(Vicari 2014:92), users are more likely to be exposed to the same information and to spread pieces of content seen elsewhere within their 'own' community, than in the absence of these links. Thus, denser areas of recognition do not constitute a flow of information per se, but surely facilitate this flow[57]. Thus, the following section will explore the recognition network on the meso-level of subgroups or communities.

The identification of subgroups may be driven by an a-priori knowledge of actors and an expected community structure and thus be used as a confirmatory analysis. In other cases, such as this, it may be driven by the researcher's interest to understand a network, reveal community structure, and interpret the results in an exploratory process. Used like this, community detection lends itself well to a deeper exploration of graph-level properties such as density and fragmentation. For the detection of communities in networks, a number of different algorithms have been developed, based on decomposing a graph by a stepwise deletion of ties with the highest edge-

[57] Table IV.26, later in this thesis, will also show, that the adjacency matrix of recognition and information sharing are significantly correlated, meaning that groups who are connected in one network, are also connected in the other.

betweenness (Girvan and Newman 2002), by maximining the modularity[58] of partitions (Clauset et al. 2004), by random-walks along the edges of a network (Pons and Latapy 2005), or by using a map-equation focused on flow in networks (Rosvall, Axelsson, and Bergstrom 2009). These algorithms differ by the types of network properties they can handle (directed/undirected, weighted/unweighted, number of components) and by their computation time (see Lancichinetti and Fortunato 2009 for an overview). While I do not find it helpful to dig deeper in the technicalities of the various algorithms for the purposes of this thesis, it must suffice to say that I tested several algorithms implemented in the network analysis package *igraph* (Csardi and Nepusz 2006), used the algorithms that are designed to handle the properties of the data, and report results that are most interpretable. Table IV.6 reports the results of a community detection using the Infomap algorithm (Rosvall et al. 2009) on the one giant weak component (nodes=156) of the recognition network, including only the three communities with a membership of at least eight groups. The table sums up the results of this community detection, reporting some of the already introduced measurements to describe the structural properties of each of the three biggest communities separately.

Table IV.6 Structural properties of communities of size >8 in the recognition network

Measure	C1	C2	C3
Nodes (fraction of Component)	118 (.75)	8 (.05)	8 (.05)
Internal Edges (fraction of Component)	409 (.71)	16 (.03)	10 (.02)
External Edges (fraction of Component)	99 (.17)	34 (.06)	28 (.05)
Density	.03	.29	.18
Reciprocity	.17	.38	.2
Average Path Length	3.05	1.33	2.03
Centralization (in-degree)	.10	.43	.39

[58] The Modularity score Q, seeks to inform the researcher about a significant departure of the assumed partition of a network against a null model with a random structure.

Centralization (out-degree)	.35	.29	.25
Transitivity	.21	.51	.15
Average edge length in km	274	129	.189

Firstly, it seems that a vast majority of nodes are placed in one big community, C1, comprised of 75 per cent of all connected nodes. *Secondly*, this community is remarkably similar to the overall network, with only slightly higher values in density, centralization, and transitivity, and slightly lower values in reciprocity and average path length. In addition, the average length of an edge in kilometers is similar to that of the overall network. C2 on the other hand exhibits a higher value in reciprocity and transitivity, meaning that the eight groups of this community are densely (.29) and mutually interconnected, leading also to triadic closure and small path lengths. Nonetheless, this community is by far more in-degree centralized than the overall network is, meaning some groups are vastly more popular than others in this community are. However, this community is not separated from the rest of network, as the 34 external ties, i.e. ties that connect nodes in this community to nodes in other communities indicate. C3 that also consists of eight groups, lies somewhere in the middle between C1 and C2, as the measures are concerned. In summary, we may interpret these results as a structure, in which only very few groups seem to form very few dense clusters, that almost seem to show properties of "fan-clubs", like C2. Figure IV.15 illustrates the two smaller communities. In this visualization, nodes are placed by the force-based Fruchterman Reingold algorithm[59] (Fruchterman and Reingold

[59] In this case, the algorithm yields very similar results to a visualization based on multidimensional scaling (MDS) of geodesic distances. One of the advantages of MDS is that distances in the plot can be clearly interpreted. It's disadvantage however is that it results in overlapping nodes which is why a less "accurate" but aesthetically more pleasing layout algorithm is often preferred (Borgatti et al. 2013).

1991) for network visualization. Node size is proportional to the total degree of a node in the *entire* network. Square-shaped nodes represent the groups from Hessia in C2 and from Bavaria in C3, while all other nodes are circle-shaped. The figure tells us that in both cases, geographic proximity (in the sense that four (C3) and five (C2) out of eight groups are from the same geographic area) seems to play a role for cohesion. While there is an extensive debate about spatiality in networks (Gould 1991; Hedström, Sandell, and Stern 2000; Nicholls, Miller, and Beaumont 2013), in this thesis I will not enter this discussion in detail, but rather assume a naïve understanding of geographic proximity and investigate how it corresponds to a network's structure. If we take the average length of an edge, measured in kilometers, both C2 and C3 have shorter average lengths then the average of the network[60]. At least for C2, this finding is significant and indicates, that in this case, community structure corresponds to geographic proximity. This proximity in spatial terms also seems to be associated with reciprocity, meaning that among the Hessian groups, it is more common to be aware of each other and return a positive nomination than in other groups. The algorithm has also placed the most popular overall node DE03 in this community, which explains the in-degree centralization of this community. C3 that consists of mostly Bavarian groups is also centralized around a group BY01, albeit with important differences: BY01, as the node size shows, is not as connected in the entire network as DE03 and BY01 is not only on the receiving end of recognition. Instead, we can see that it does reach out to two Saxon groups within the community, which do not reciprocate the

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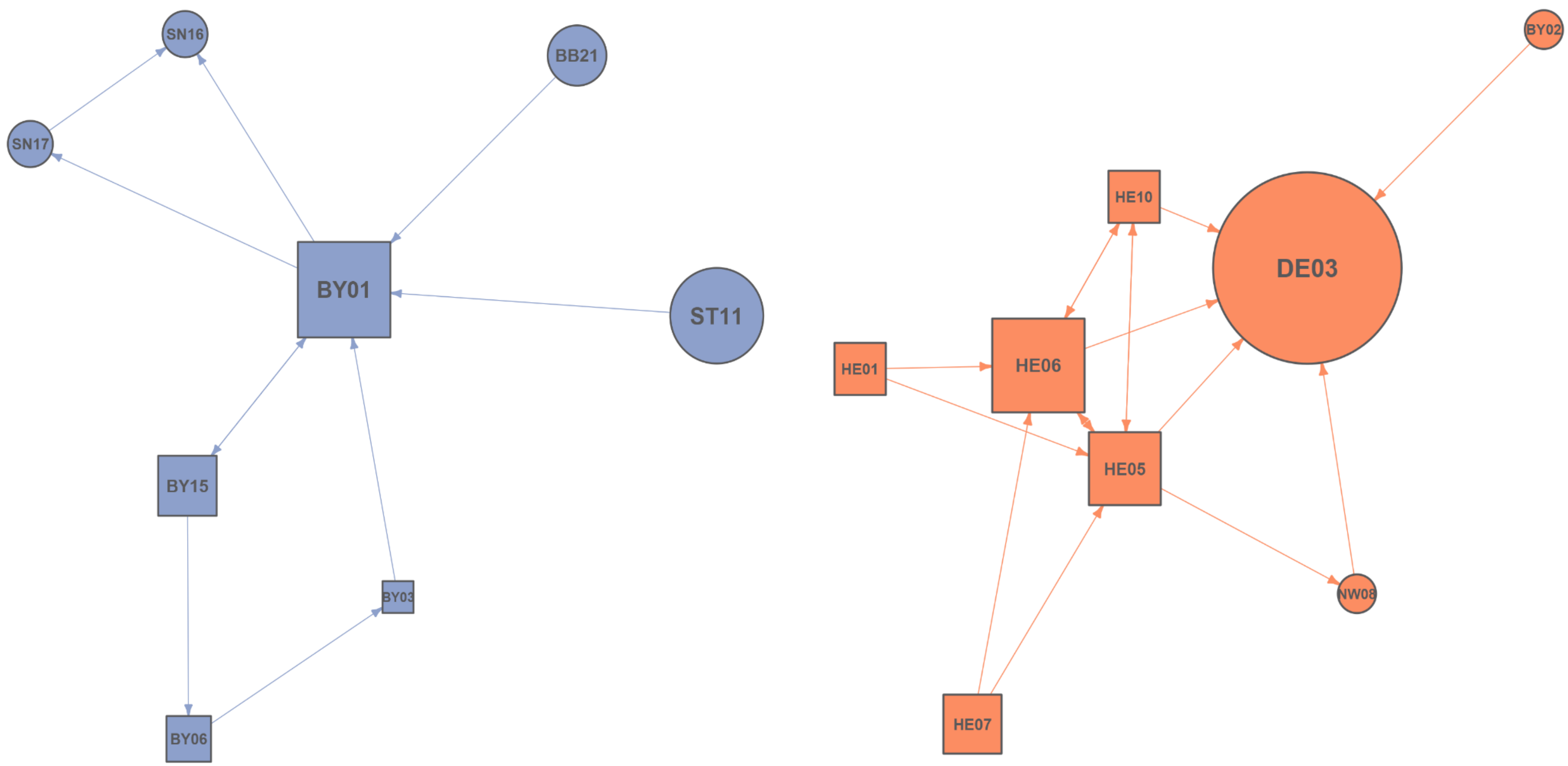
[60] If we apply a permutation test and draw 5,000 random samples of 16 (C2) and 10 (C3) edges of this network, only .04 per cent (C2) and 16 per cent (C3) of the samples have a shorter average length. At least for C2, we can thus assume that groups are significantly closer to each other in spatial terms than expected by chance (Although the placement of the Germany-wide group in the centroid of Germany slightly distorts this measure).

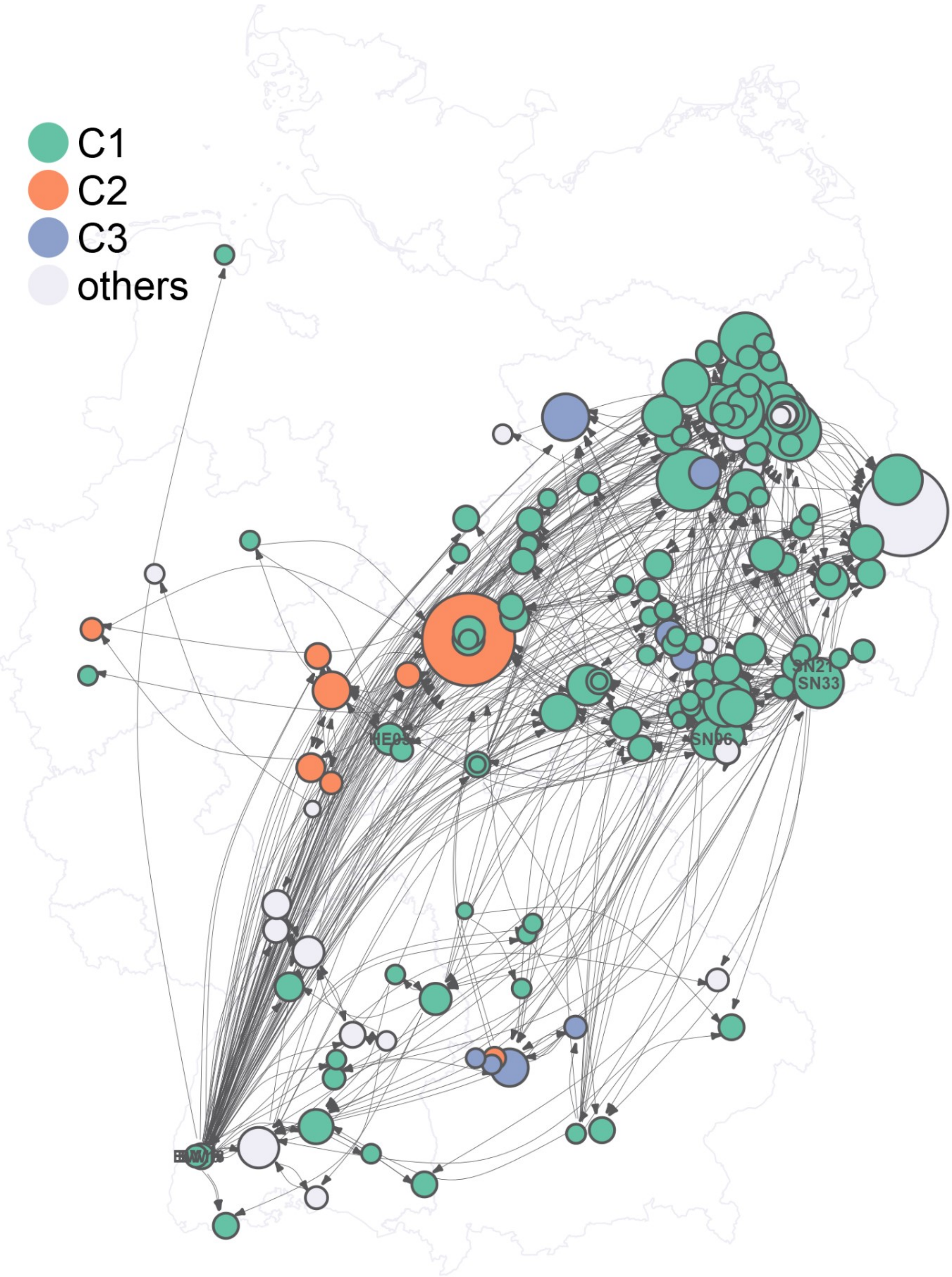
effort. In that sense, BY01 is not the center of a “fan-club” as DE03 but may rather act as a regional bridge between Bavarian and other groups. However, even if this investigation of two smaller communities serves to illustrate trends and tendencies, it must not be over-interpreted, as we must not forget, that both communities are not as separated from the rest of the network, as the visualization may imply, but the nodes of C2 and C3 hold 34 and 28 ties to other nodes outside the communities. Therefore, the entire network is not clearly structured along community lines, as the relatively low modularity score of Q=.16 explains. Figure A.6 in the Appendix features an MDS-Layout of the entire network (without isolates) that shows how even the smaller more cohesive communities are still relatively well connected in the entire network, that does not seem to be strongly divided among community-lines..

Figure IV.15 Communities C3 and C2 in the recognition network



What is more revealing of an underlying structure in this network is Figure IV.16, in which the nodes are placed according to their geographic position on a map of Germany. In this figure, node size corresponds to in-degree and nodes with more than 20 outgoing connections are labelled. The colors represent communities C1-3, with all other nodes colored white. We can see that on a map of Germany, the eight groups of C2 (orange) are mostly in central Germany (Hessia), while the eight groups of C3 (blue) are split between the already discussed Bavarian groups and those in East-Germany. The added value of this figure is that it reveals a geographic pattern behind the divide of receiving and giving recognition that was discussed earlier. The overlapping labels in the South-West have many outgoing links, but as the node size indicates, they receive almost no recommendations themselves. The groups with relatively many in- and outgoing links, i.e. labelled nodes of moderate size, are placed in Saxony with the SN-labels. The two large nodes DE03 in the center and BB31 receive most recommendations without giving any themselves. While these two surely stand out, we can see that many other popular groups seem to be located in (Northern) Brandenburg and Berlin. On the other hand, groups in the West and South almost all receive very few recommendations, as their smaller node size indicates.

Figure IV.16 Geographic layout of the recognition Network



Therefore, the key finding in terms of identifying structural patterns in the giving and receiving of recommendations is not one of a strong division between internally cohesive communities but one that underlines a clear geographic divide between popularity and outreach, with especially the former more prevalent in Germany-wide or Eastern-German groups. With these findings about structural patterns in the overall network, in communities and on key actors within this network, we will focus our attention toward a comparison of other types of ties that can serve to operationalize the various aspect of resource exchanges. Therefore, the following two subchapters will illustrate practices of information sharing and co-mobilization for events and thus allow a comparative perspective on how different groups make use of the different affordances of SNS and what patterns emerge from these interactions.

Information Sharing

The second type of network that I group under the mechanism of resource exchange, is information sharing. Sharing in the sense used here, does not mean group A actively provides any piece of information to group B, but rather means both groups share the commonality of having access to and having actively debated a piece of information, be that an image, a video, or a newspaper report. We may reasonably assume that a highly active group, whose members collect and debate pieces of content, may be seen by others as a source of information to look to and may thus influence the formation of opinions, or guide attention to issues and events. Collective action studies have frequently highlighted the role of information dissemination as one important function in the organization of and mobilization for joint action (Bennett and Segerberg 2013). In Diani's application of the MoC framework (2015), "sharing information" is an explicit survey question to qualify ties that represent the dimension of resource exchanges. Thus, a network of mutually shared pieces of information represents exactly those aspects, those stories, those newspaper reports, memes, digital leaflets, etc. that do not remain within the confines of a single group but are collectively ascribed with importance and meaning for the joint cause and thus are henceforth influential across groups. To operationalize information sharing, I ran a search for regular expressions that capture every "http://" or "ftp://" hyperlink over the entire data of messages, meaning all posts and comments on the pages of all 185 AAS-groups. Before mapping these data to a *network* of information sharing among AAS-groups, these hyperlinks themselves and their usage and importance by and for different groups may enrich our understanding of AAS-groups, in terms of how they use linking, what they debate, and what captures their attention.

Table IV.7 Hyperlinks in AAS-groups

Hyperlinks	
Total	110,432
Unique links	84,075
Shared links	14,553
Per group mean	597
Per group median	220
Per group range	[2 - 14,409]

Table IV.7 provides a first overview of the usage of hyperlinks in AAS-groups. *Firstly*, we can see that linking is a common practice, as in total, we find 110,432 hyperlinks embedded in posts and comments. However, as total activity varies across groups (see

Figure IV.2 in a previous section), it is not surprising that *secondly* the use of hyperlinks varies from as low as two to a maximum of 14,409 in a single group. Thus, from an average of 597 links per group but a median 220 of links per group, we can conclude that many groups make moderate use of hyperlinks and few groups make exceptionally heavy use of linking information. *Thirdly,* the table shows that groups do not remain confined to isolated ecologies of linking but that only 84,075 links in the data are unique, meaning they appear only on one page alone. In turn, 14,553 unique hyperlinks can be found in *at least* two different AAS-groups, providing the substance of the information sharing network that will be analyzed in this section. Before we turn our attention to the structural patterns of information sharing among groups that arise from this co-linking practice, I want to continue the investigation of hyperlinks themselves, to foster our understanding of the actual substance and content that forms the information ecology of AAS-groups.

In order to study this ecology, the first step of data manipulation involves extracting the domain from each hyperlink. While an analysis on the level of domain instead of hyperlink has the downside of any aggregative step, meaning a loss of resolution, it also provides important advantages. *Firstly*, it cancels out *noise* in the data, meaning that a link to the same piece of information can contain many additional elements, for example so-called “Urchin Tracking Module” elements, that contain tracking information. While in principle it is possible to harmonize these elements, I find it easier and sufficient for this digression in my analyses, to “cut-off” each hyperlink after the domain. *Secondly*, the aggregation to domains provides a clearer and more straight-forward picture of which *types* of sources are pivotal for AAS-groups, allowing a look that is more focused on media ecosystems (Benkler, Faris, and Roberts 2018) rather than singular stories. Therefore, I used to R-package “urltools” (Keyes et al. 2018), to disassemble the hyperlinks into their elements and extract only subdomain and top level domain. In additional steps, I excluded the “www.” from each domain, as well as signifiers of the mobile version of a website, like “m.” or “mobil.” in front of the domain. Thus, a link like “https://www.openpetition.de/petition/online/sofortige-abschiebung-auslaendischer-salafisten-islamisten” simply becomes “openpetition.de”. This reduction yields 2,588 unique domains that were used among AAS-groups. The frequency of these domains is, as we would expect, unequally distributed, as the “internal” content, like photos, videos, and posts themselves, are all grouped under the domain “facebook.com”, that appears 40,348 times. One the one hand, it means that members in AAS-groups produce significant amounts of “own” content instead of reproducing external information. On the other hand, for this analysis it is thus more meaningful to look at domains external to the Facebook-platform, as Figure IV.17 does. The chart is ordered from top to bottom by the total amount of links to each domain, which is also the value of the x-axis. These top-24 are overwhelmingly dominated by the domains of news-websites, with the notable exception of the video-sharing platform YouTube. This tells us that the external information that circulate among AAS-groups is largely comprised of articles from various German news websites. The top-domain is focus.de with 4,481 links. The print version of Focus magazine is one of the most popular weeklies in German press. It's popularity among AAS-groups may partially be explained by a controversy around the magazines coverage of the already mentioned sexual attacks in Cologne on New Year's Eve 2015. Focus reported about the incidents with a cover showing a naked white woman with black handprints all over her body under the heading "Women accuse – After migrant sex-attacks: are we still tolerant or already blind?"[61].

Perhaps unsurprisingly, most of the top news websites in Figure IV.17 were mostly critical in their coverage of migration and asylum, with conservative news outlets from the publisher "Springer" like "Welt" and the tabloid "Bild", as well clearly right-wing news outlets like "Junge Freiheit", "Epoch Times", "Netzplanet", or "PI-News". More mainstream media like "SZ-online" or left-leaning newspapers like "Tagesspiegel" are not as popular in terms of the volume of links, but still make it to the list. Thus, we can assume that AAS-groups do not form isolated "echo-chambers" oblivious to any mainstream discourse, but in turn follow the logic of a counter-public (Downey and Fenton 2003), well aware but highly critical of mainstream or oppositional discourse (Kaiser and Puschmann 2017). The final insight to the actual content of links is given in Figure IV.18.

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[61] Original German: "Frauen klagen an – Nach den Sex-Attacken von Migranten: Sind wir noch tolerant oder schon blind?"

Figure IV.17 Top-24 domains (without Facebook) among AAS-groups by frequency

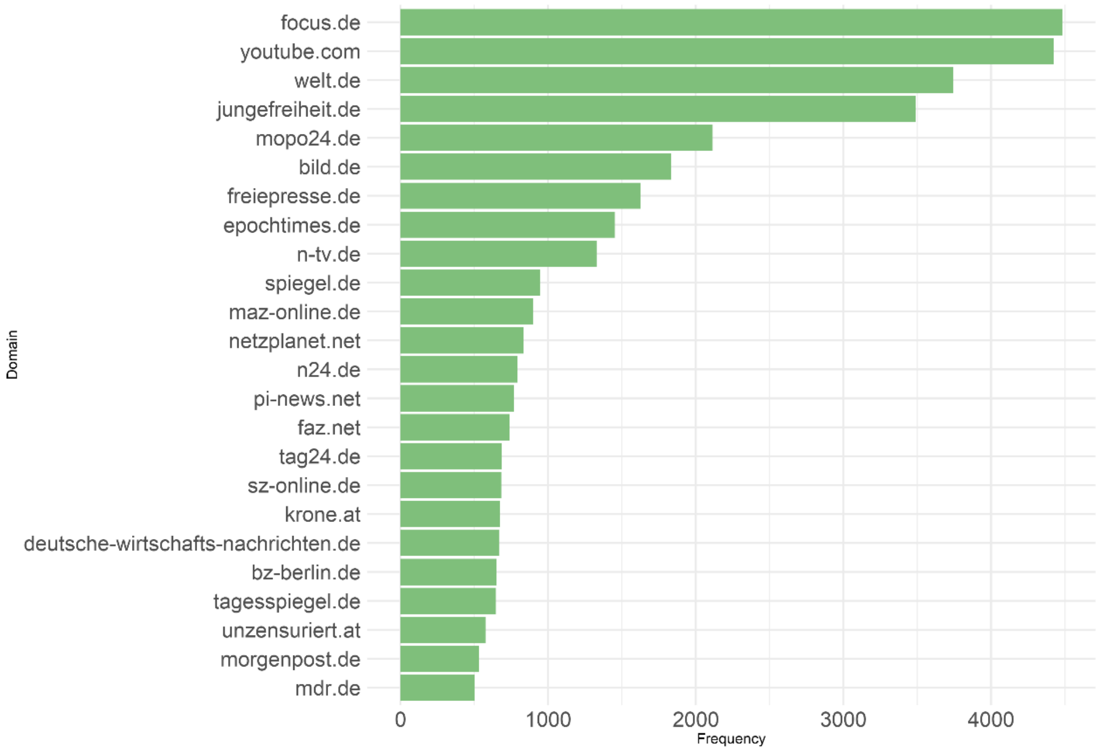
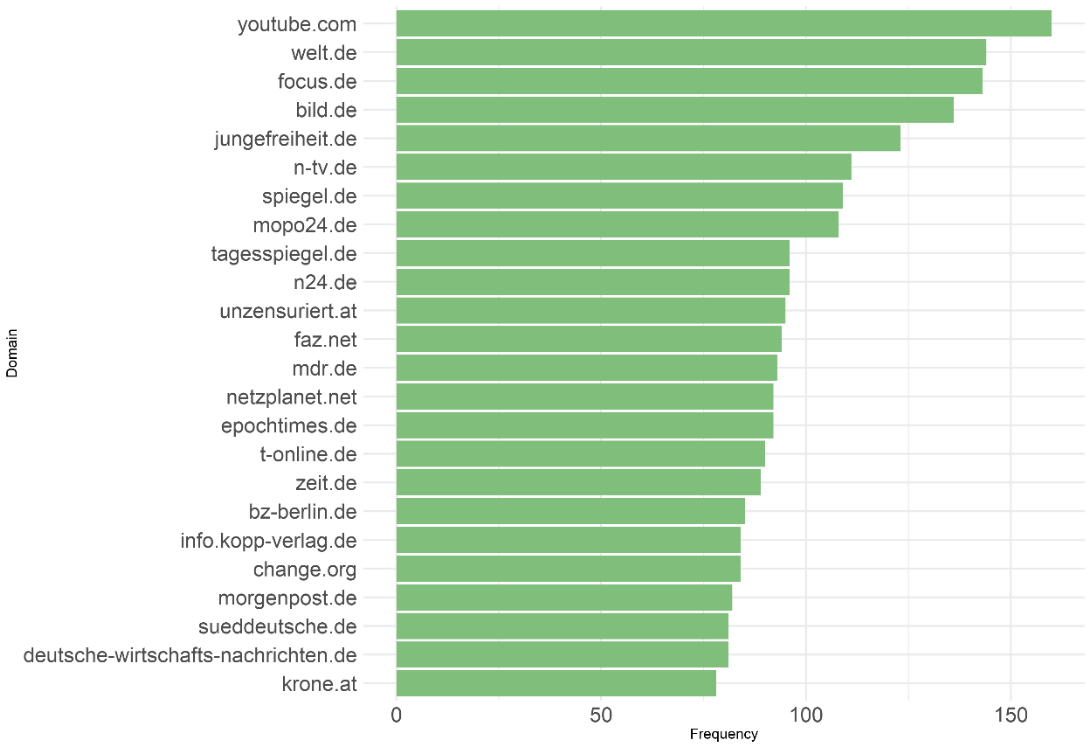


Figure IV.18 Top-24 domains (without Facebook) among AAS-groups by number of AAS-groups



This chart follows the same logic as Figure IV.17 but with the x-axis illustrating the number of different AAS-groups that linked to the respective domain, as an additional measure of popularity, that is not based on raw counts but instead the co-appearance of a domain in multiple AAS-groups. The very similar composition and the overall high values show that those domains who are central in terms of absolute links are also the ones that span across most AAS-groups. It is notable however, that this measure of the *reach* of a domain through the population of AAS-groups is more equally distributed than the *raw popularity* measure in the previous figure. This also means that news outlets like “Tagesspiegel”, “Zeit”, or “Sueddeutsche”, who are likely to report more nuanced and less radicalized about issues pertaining migration and asylum, are nonetheless cited by almost as many AAS-groups as more conservative and right-leaning outlets are. This fits well with the above mentioned concept of counter-publics and with the popularity of the “lügenpresse”-discourse in the chapter on content analysis, meaning that despite the clearly radical views expressed by members of AAS-groups, they are not detached from a mainstream news ecosystem, but instead are likely to follow and (critically) debate information from various sources[62].

Summing up, we can note that the following analyses of a network of information sharing among AAS-groups is likely to reflect both the proximity of groups in terms of “external” information pieces, meaning their consumption and discussion of (online) newspaper articles and YouTube videos, as well as in terms of “internal” information pieces, meaning user-provided content within the Facebook-

[62] The tendency to select news sources from opposing political standpoints and regardless of the sources’ argumentation has also been described by Hagen (1993) as the search for “opportune witnesses”.

platform. Thus, information sharing as we understand it here, represents a shared link ecology, mostly in the form of media ecology, as the dominance of news websites suggests. While this surely touches controversial debates of political polarization in general and selective exposure and echo chambers in particular (Bruns 2017; Dubois and Blank 2018; O'Hara and Stevens 2015), I believe it suffices for the sake of this dissertation to assume that a network built by acts of (re)posting the same links can be understand as of creating a "*shared social media news agenda*"(Bright 2016). Thus, on the one hand the (co-)creation of such an agenda ensures that even passive users are exposed to the same stories and images and on the hand, it produces a common repertoire of information that AAS-groups can draw from in solidifying their internal beliefs and signaling those to the outside world.

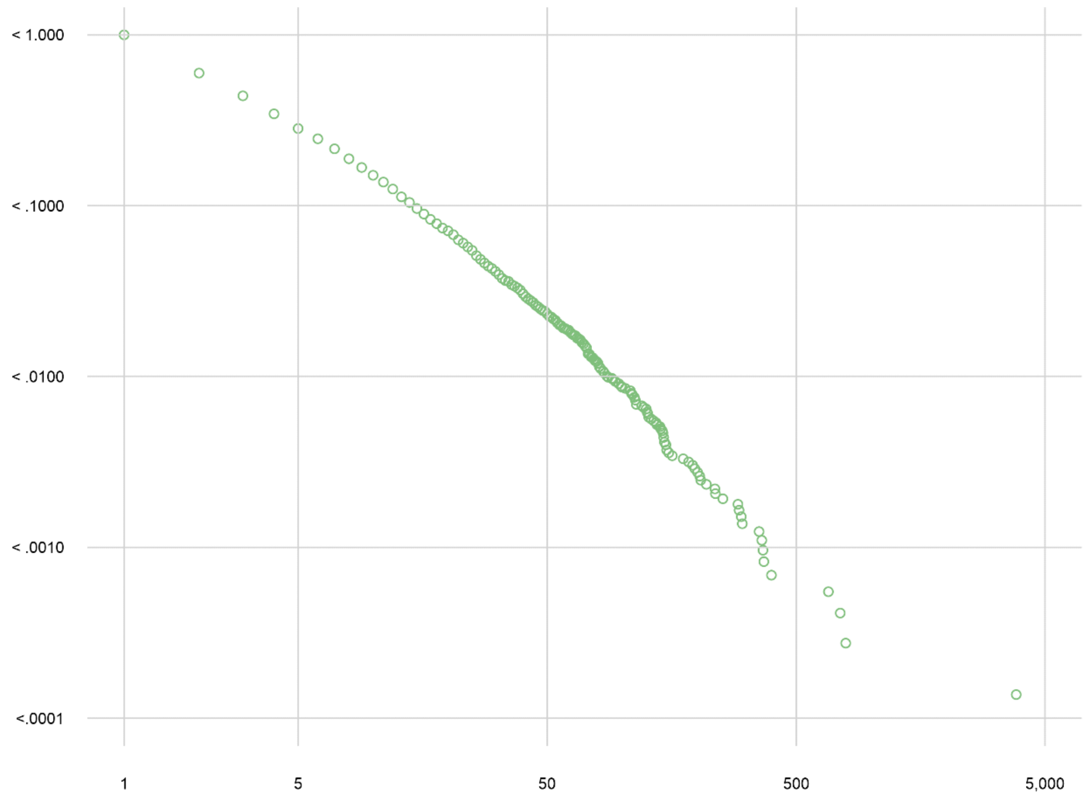
Network Construction

The analysis of this networks requires a few steps of data manipulation that need explanation. *Firstly*, each of the 110,432 pairs of hyperlink and AAS-group was treated as an edge of the network, which thus consists of 84,260 (i.e. the number of unique hyperlinks plus the number of AAS-groups) nodes. This is a two-mode network, meaning that edges exist between two different types of nodes, namely AAS-groups and pieces of information, but never between nodes of the same type. This network can be represented by a dichotomous matrix of dimensions 185*84,075 in which each cell contains a one or a zero depending on whether or not a given AAS-group has linked to a given piece of information. *Secondly*, transposing this matrix and multiplying it with the original yields a symmetrical weighted matrix of dimensions 185*185 in which each cell contains the number of common pieces of information that were shared by both the group in the row and the group in the column in this matrix.

In other words, this similarity matrix represents the one-mode projection of a two-mode network. This network is both *undirected*, meaning it expresses not directionality but commonality between two nodes and *weighted*, meaning the strength of each commonality can be quantified through an edge's weight. This weight, however, is unequally distributed, as Figure IV.19 illustrates.

In this visualization we can read the x-axis as the weight of an edge and the y-axis as the probability of any given edge to have at least this weight. Each datapoint represents one of the 7,273 edges in this network. As the doubly logarithmic scale implies, very few edges are very heavy compared to the many edges that possess comparatively low weights and thus a higher probability in the plot. In fact, 2,929 of the edges hold a weight of only one, meaning they connect two AAS-groups that shared only one piece of information.

Figure IV.19 Empirical complementary cumulative distribution function (CCDF) of weight for 7,273 edges in the information sharing network.



We thus observe a behavior typical of networks generated from online interaction, in which the most common connection is a weak one and the distributions are not well described by measures like the mean or the standard deviation, as values are not clustered around a typical value (Clauset, Shalizi, and Newman 2009). Instead we can speak of heavy-tailed distributions that span several orders of magnitude and do seem to approximate log-normal or power-law distributions rather than exponential or Poisson distributions, meaning that even though exceptionally large weights are rare, they are much more common than we would expect from assuming exponential decay or even a normal distribution. The properties of this network are summarized in Table IV.8.

Table IV.8 Properties of the information sharing network

Network Properties	
Nodes	185
Isolates	0
Edges	7,273
Density	.43
Range of edge weights	[1 – 3,827]
Mean edge weight	7.85
Median edge weight	2

To detect, analyze, and visualize structural patterns in such a network where almost every node is weakly connected to every other node (Density=.43), several scholars have highlighted the importance of edge-based data reduction techniques (González-Bailón and Borge-Holthoefer 2016; Mukerjee, Majó-Vázquez, and González-Bailón 2018; Neal 2014). The simplest approach is to apply a naïve threshold for edge weights, removing any edge below a certain weight. The underlying logic is that low weights in projections of affiliation networks represent ephemeral connections and are unlikely to reflect to stable, long-lasting, and strong overlaps.

While this is certainly true, it ignores the fact that actors' properties like strength of membership or duration of activity that limit the maximum number of affiliations of each actor, might be unequally distributed. In this case, this certainly applies to the number of total activities per AAS-group, as the discussion on

Figure IV.2 in an earlier chapter has shown. For a network of information sharing, an edge weight of 25 may be considered a strong connection for a group with, say, 1,000 total activities. For a group with 10,000 activities however, 25 may mean a weak connection. Thus, "*controlling for this local disparity requires […] defining a null model to determine what counts as an exceptional connection, i.e. a significant departure from randomness, considering that connectivity in networks varies significantly from node to node*" (González-Bailón and Borge-Holthoefer 2016). The logic behind this approach is to "*essentially shift the nature of co-affiliation data from frequencies of co-occurrences to tendencies or revealed preferences to co-occur*" (Borgatti and Halgin 2014:426). While applications based on e.g. Jaccard Coefficients have been in existence for some decades, more recent developments by Serrano et al. (2009) and Coscia and Neffke (2017) have proposed an extraction of the *backbone* of weighted networks based on normalizing the weights for each edge between node i and the adjacent nodes and comparing the empirical weights to randomly assigned weights from a uniform distribution. This yields a measure of probability of existence of each weight against a null model and conventional p-values can be used as thresholds. Thus, as the *third* step of data preparation, I implemented Serrano and colleagues' backbone extraction algorithm in the Python programming language to calculate the so-called alpha values and used a threshold of α=.1 to filter out any edges above that score. The properties of the resulting network which will be the object of the following analysis, are summed up in Table IV.9.

Table IV.9 Information sharing network before and after backbone extraction

Network Properties	Before Reduction	After Reduction
Nodes	185	185
Isolates	0	26
Edges	7,273	941
Density	.427	.055
Range of edge weights	[1 – 3,827]	[3 – 3,827]
Mean edge weight	7.85	39.9
Median edge weight	2	19

We can see that the number of edges (and hence density) is greatly reduced in the network's backbone. The lowest weight in the reduced network is now three, meaning that any edge of weight one or two also had alpha values of above .1. This leads to a new mean weight of almost 40 and a median that is still lower than the average, yet not to such a degree as before reduction. Ideally, these procedures of data manipulation and reduction will allow to flesh out the structural patterns in the practice of information sharing among AAS-groups more clearly.

Graph

The measures applied to assess the properties of the entire network of information sharing are similar to the ones used to inspect the recognition network, with adjustments made due to the undirected but weighted nature of the former. Table IV.10 presents the results in a comparative perspective.

Table IV.10 Structural properties of the recognition and the information sharing networks

Measure	Recognition	Information Sharing
Directed	Yes	No
Weighted	No	Yes
Edges	579	941
Range of edge weights	n.a.	[3 – 3,827]
Mean edge weight	n.a.	39.9
Total edge weight	n.a.	37,542
Density	.017	.055
Reciprocity	.18	n.a.
Isolates	29	26
Fraction of Isolates	.16	.14
Components (isolates excluded) weak/strong	1/3	1
Maximum Component Size weak/strong	156/53	159
Average Path Length	3.67	2.42
Connectedness weak/strong	.71/.08	.74
Centralization (in-degree)	.12	.46
Centralization (out-degree)	.29	.46
Transitivity	.20	.32

From these measures we can deduce that the information sharing network is more cohesive than the recognition network. While almost six percent of all possible edges are realized, only 14 percent of nodes remain unconnected to any other node. Those who are connected are so in one single giant component, whose density (not in table) is .075. This corresponds to an average path length of 2.42, and a connectedness of .74. In substantial terms, this means that AAS-groups are not separated by producing and debating different information but instead seem to be fairly homogeneous in their information sharing. With the exception of the 26 isolated groups, all nodes are connected by linking to an average of almost 40 shared pieces of information. At the same time, the network seems to be both more centralized (.46) and more clustered (.32) than the recognition network. This higher centralization may be the result of a more instrumental logic at work: We can well imagine a generally homogeneous set of organizations, like AAS-groups, to (happily) rely on few central distributors of information, as in the absence of deviant discussions or opinions, there is little need for alternative hubs of information. The fact that all groups are connected in one component can support this assumption, which also fits well with the results of our content analysis in chapter IV-ii: There, we found that discussions rather serve the purpose of reiterating and fostering preconceptions and frames rather than openly deliberating an issue from various, contrasting angles. In general, this centralization means that despite high cohesion in the overall network, we may look at inequalities within the network, that can be revealed by an inspection of node-level measures in the following section.

Nodes

Unlike the recognition network, we cannot distinguish between in- and outdegree in the information sharing network. Nonetheless, an unweighted measure of degree, i.e. the number of other groups with which one group shares information, can inform the researcher about central actors within a network, i.e. those with more opportunities to influence others.

Figure IV.20 Histogram of degree distribution in the information sharing network

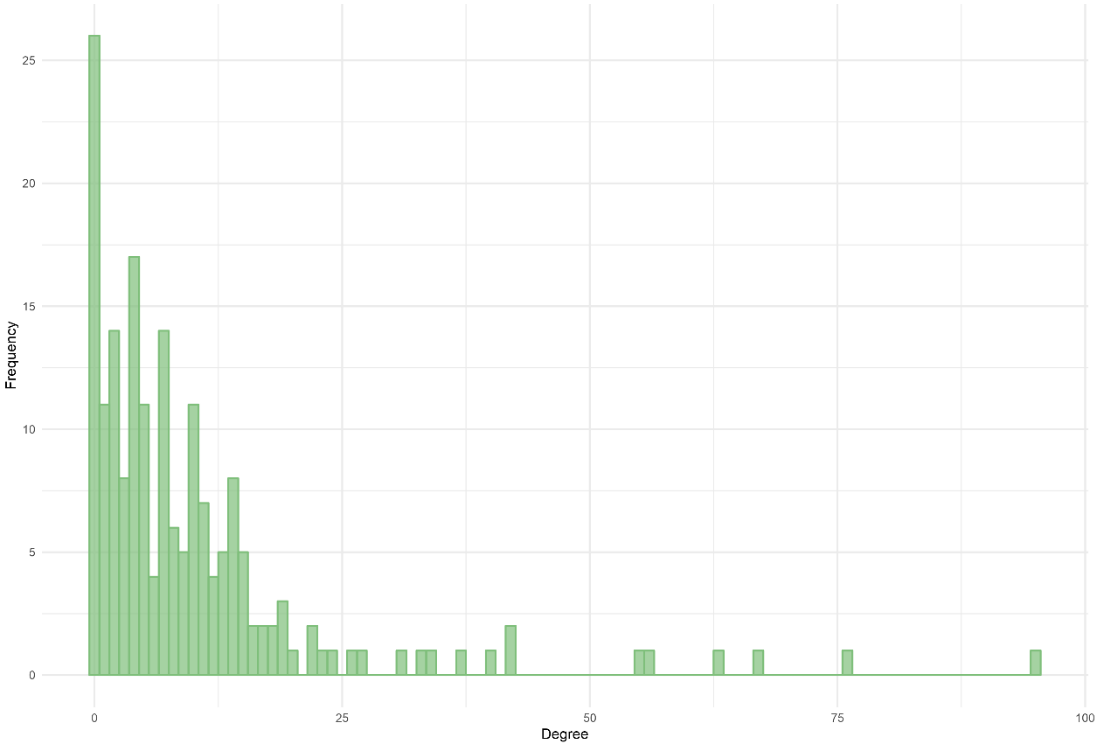


Figure IV.20 gives an indication of how degree is distributed across AAS-groups. The highest bin contains the 26 isolated nodes with degree zero. From then on, we can see that for most groups, *degree centrality* ranges between one and 30, with a few outstanding exceptions. Six groups are each connected to more than 50 other groups through information sharing, with a maximum value of 95. It is this unequal distribution of centrality that explains the high score for centralization in the graph-level analysis. The groups with the highest values (in descending order) are SN33, SN06, TH01, BW19, BB31, and BB26. Given that ties in this network are weighted, we can additionally introduce measures of weighted degree centrality, either through the combined weights of all edges adjacent to a node or through the average weight of all edges adjacent to a node (Borgatti et al. 2013). The former measure produces the exact same order for the top-four groups with total weights of 7,552, 6,876, 2,841, and 2,646, meaning they are not only connected to many other groups, but also that they are very active in sharing information. A look at the latter measure of average tie strength however reveals that none of the groups associated with many connections and overall strong connections can be found within the top-ten. In fact, the ten groups which share more than 100 pieces information in an average tie all have at maximum 15 ties. In turn, this means that there seems to be no immediate connection between having many ties and having strong ties.

Three of the above mentioned most connected groups already featured prominently in the analysis of the recognition network, albeit in different ways. Both Saxon (SN) groups scored high in terms of outreach, while one of the Brandenburg groups (BB) scored high in terms of popularity. While all three groups share information with many partners, the *total and average amount* of information shared through these ties is substantially higher for the SN groups than for the BB group. As the ties in this network are undirected, we can only speculate about the substantive interpretation of this fact – we might however reasonably assume that the high sharing volume may again be a result of these groups' quest for attention, as they frequently reproduce content they find in other groups. In other words, groups who did not receive as much attention in the recognition network make higher use of their ties in the information sharing network. Indeed, if we apply a simple linear model to inspect the relationship between popularity, outreach, and the average volume of information sharing for each group, we find a positive, significant association between outreach and information sharing. This supports the speculation that attention-seeking is a driving mechanism behind a group's activation of tie potential in terms of the volume of information sharing. However, we must remain careful in this kind of interpretation, as the data at and does not allow to clearly state where pieces of information originate and where they travel. Therefore, we will leave the investigation of single nodes at this point and turn attention to the discussion of subgroups in the information sharing network.

Communities

To identify cohesive subgroups of information sharing, I applied the Infomap community detection algorithm (Rosvall et al. 2009) to the biggest component (nodes=159) of the network. In total, the algorithm was able to identify a more clear-cut community structure than in the case of the recognition network, with a modularity value of Q=.49. Of the 13 communities that the algorithm identified, Table IV.11 sums up the structural properties for all subgroups of at least nine members.

Table IV.11 Structural properties of communities of size >8 in the information sharing network

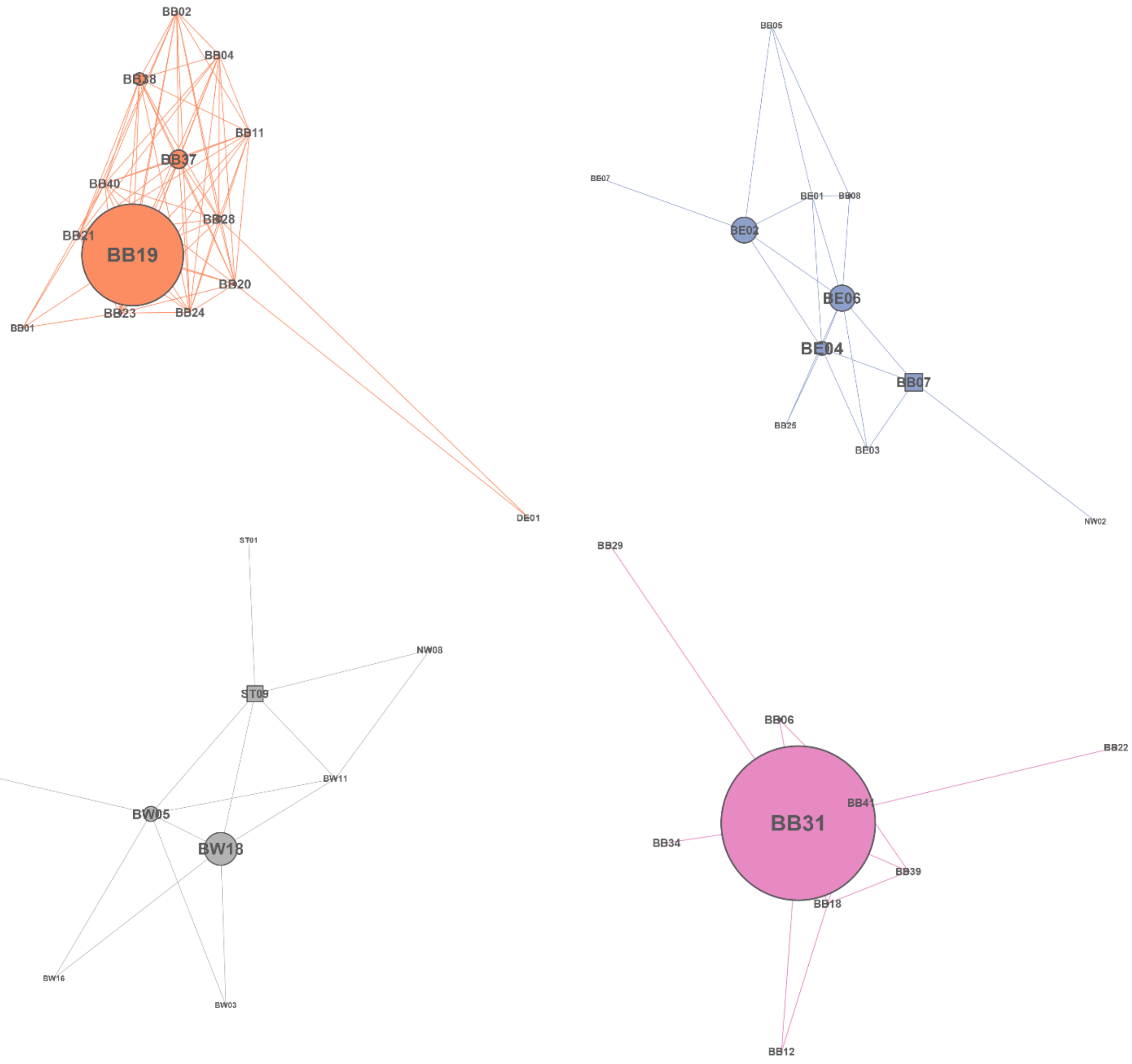
Measure	C1	C2	C3	C4	C5
Nodes (fraction of Component)	79 (.50)	14 (.09)	11 (.07)	9 (.06)	9 (.06)
Internal Edges (fraction of Component)	483 (.51)	72 (.08)	20 (.02)	13 (.01)	14 (.01)
Total weight of internal edges (fraction of Component)	19,038 (.51)	6,948 (.19)	546 (.01)	401 (.01)	118 (.00)
Mean weight of internal edges	39.42	96.5	27.3	30.85	8.43
External Edges (fraction of Component)	199 (.21)	59 (.06)	51 (.05)	80 (.09)	53 (.06)
Total weight of external edges (fraction of Component)	4,028 (.11)	1,299 (.03)	1,035 (.03)	1,683 (.04)	891 (.02)
Mean weight of external edges	20.24	22.02	20.23	21.04	16.81
Density	.16	.79	.36	.36	.39
Average Path Length	1.96	1.22	1.90	1.64	1.78
Centralization (degree)	.69	.13	.34	.64	.36
Centralization (betweenness)	.26	.06	.26	.74	.34
Transitivity	.39	.93	.50	.40	.48
Average edge length in km	267	56	47	83	257

It is the nature of communities to be denser than the overall network. Still, community C2 stands out by having realized 79 per cent of all possible (internal) edges. This goes hand in hand with a transitivity of .93, meaning the fraction of closed triads in C2. It is also the community with the highest average weight of internal edges, meaning that through an average connection within the community, 96.5 pieces of information are shared. Thus, even though the community contains only nine per cent of all nodes and eight per cent of all edges, its edges carry 19 per cent of the network's total edge weight. In addition, of the communities in the table, only C1 and C2 have more internal than external ties, meaning the members of these communities share more ties with each other than with all other groups of the network. While C1 is comprised of 79 groups, and thus half of the entire component, this behavior might be expected. For C2 however, this is more remarkable, as is consists of only 14 groups, thus having much more *potential* external ties than C1. Nonetheless, the ties that members of C2 hold to members of other communities are slightly stronger than other external ties, with an average weight of 22 pieces of information. This means we can describe C2 as a highly cohesive, strongly connected, and non-hierarchical (i.e. lowly centralized) subgroup, that holds relatively few but comparatively strong ties to the rest of the network. What is striking about C2, is that *all but one* of the AAS-groups in this community are from Brandenburg. This means that information sharing in C2 is a highly localized practice. The average length of an edge, measured in kilometers, is only 56 (network average: 238km), and thus significantly lower than expected by chance[63]. As strong connections exist to the rest of the network, we can nonetheless assume that while certain pieces of information may gain more attention locally, these groups do non remain oblivious to information in the rest of the network but are also strongly engaged in circulating information that attracts attention outside of the community. These dynamics are all but deterministic, as a look at C4 shows.

[63] The permutation test to establish significance is the same as used for the recognition network. Also see: Footnote [60]. The test also shows that edges in C3, and C4 are significantly shorter than expected, while edges in C1 are significantly longer.

Membership to this community again seems to correspond to geographic proximity, as *all* its nine groups are from Brandenburg and the average edge length in kilometers is 83, and thus significantly lower than expected by chance. However, the internal structure is by far more centralized both in terms of degree (.64) and in terms of betweenness (.74). Betweenness centralization (graph level) or centrality (node level) measure the number of shortest paths between any pair of nodes that go through each node (centrality) and the inequality of this score (centralization). A high betweenness centrality can thus mean that many actors depend on one single actor to bridge different parts of the network. Thus, on node level, it can serve to identify brokers or gatekeepers, holding power in the sense that they can influence which pieces of information pass through the network and which do not. When we turn our attention to Figure IV.21 the concept of betweenness centrality becomes clearer. The figure shows communities C2, C3, C4, and C5, plotted separately. Node position is determined by the Fruchterman Reingold algorithm, that seeks to place well connected nodes in the center of the graph. Circular nodes are those from the main geographic area of each community, while square nodes are from other regions. Label size corresponds to a group's degree centrality calculated for the entire network. Most importantly, node size corresponds to each group's betweenness centrality calculated for the entire network. This means that C4 is not only highly centralized internally, but also that the dominant actor within the community holds most of the connections to the rest of the network. While C3 and C5 are not dependent on a single group to manage the flow of information to the rest of the network, the case of C2 is entirely different. As we discussed above, the community is strongly and densely internally connected, with little tendency of centralization. However, as the vast discrepancies in terms of network-wide betweenness (i.e. node-size in Figure IV.21) illustrate, sharing information with the rest of the network is highly dependent on a single node in a powerful position. As the clustering of nodes seems to correspond to geographic proximity, we can therefore speak of actors who perform the role of regional bridges, or "*spanners*" (Borgatti et al. 2013) between groups.

Figure IV.21 Communities C2, C3, C4, and C5 (clockwise from top left) of the information sharing network

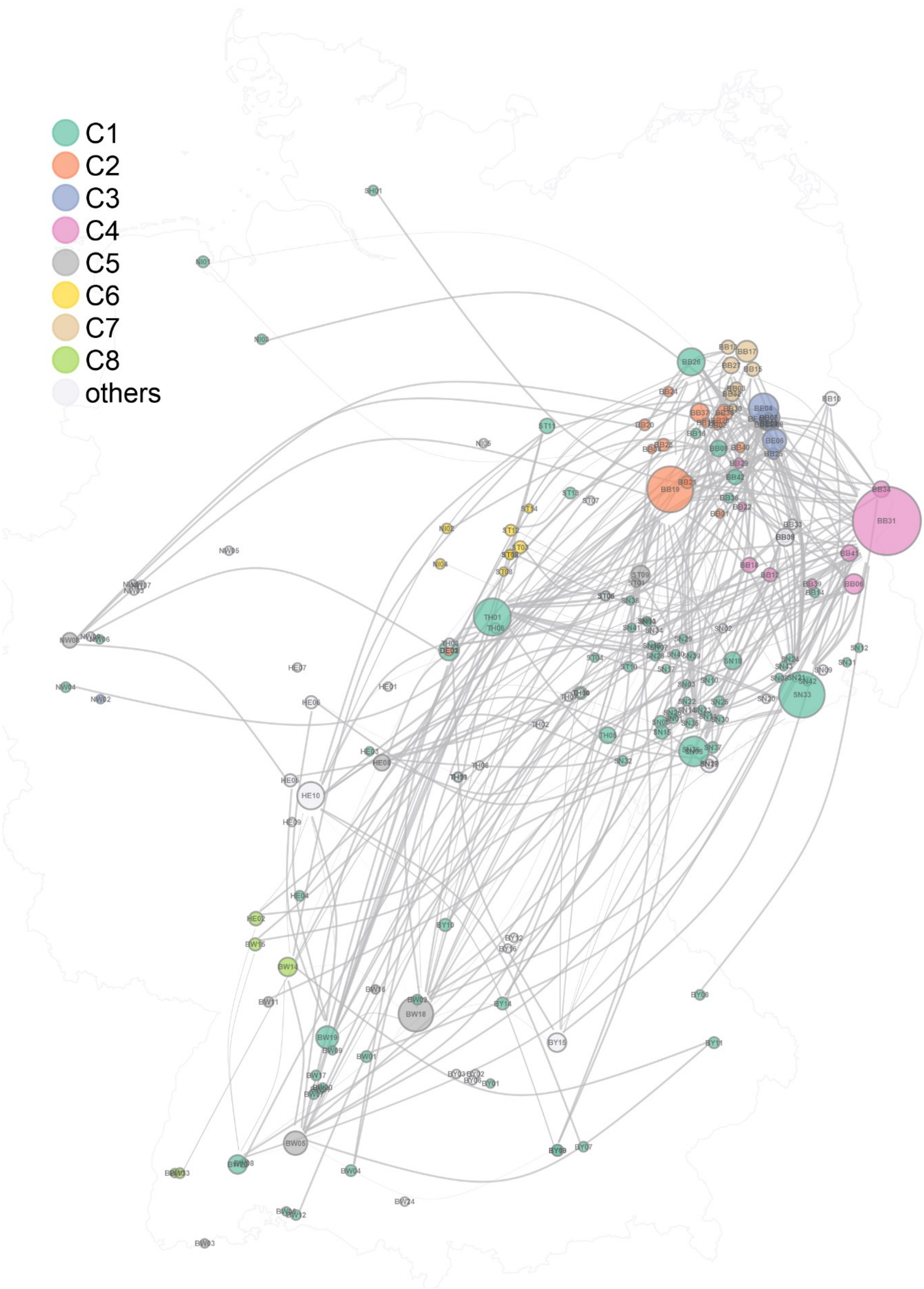


In the case of community C4, the AAS-group in that position is already known from our previous analyses: the highly popular Brandenburg-based group BB31. In the case of C2, this role is taken by group BB19, who has not yet played an outstanding role in any of the measures applied so far.

Comparing the internal structure and centralization tendencies within subgroups to the network-wide betweenness centrality score of AAS-groups forces us to take a look at the biggest community in terms of the number of groups it comprises: C1. While it is already the most centralized in terms of degree, it is also the one than contains the group with the highest overall betweenness centrality, Saxon-based SN33, which we have begun to discuss above. However, C1 does not depend on SN33 as the only bridge to other communities, as the visualization of the entire network in Figure IV.22 shows. In this figure, we see nodes laid out according to their geographic position[64], while colors represent the results of the community detection outlined above, with separate colors for the top-eight communities and a light gray for the rest. The only edges shown are those that cross community boundaries, meaning no edges exist between members of the same community in this visualization. A node's size corresponds to its degree in an imaginary graph without intra-community edges. In other words, bigger nodes are well connected to cohesive subgroups other than their own. From this figure, we can read several things: *Firstly*, the aforementioned regional clustering of AAS-groups becomes visible in its entirety.

[64] A layout based on multidimensional scaling can be found in Figure A.77 of the Appendix. It confirms the partition of the community structure, as nodes within the same community are placed in similar positions in this layout.

Figure IV.22 Geographic visualization of the information sharing network



Secondly, the measure of betweenness centrality applied in Figure IV.21 is robust, as the results match those of the degree centrality applied here. *Thirdly*, as the number of edges shows, communities are dense subgroups, but not entirely detached from each other. And *fourthly*, the largest community C1, shown in green, is scattered all over Germany. We can also see several larger nodes in C1, meaning despite its high internal degree centrality, several of its members are well connected to other parts of the network. This means, information flow is not monopolized by only actor, but depends on several groups.

Finally, before turning our attention away from the inspection of content and information sharing, I would like to close this section the same way I opened it: by looking at the actual content that circulates through the ties of the network. Since the community detection of AAS-groups revealed *localized* information sharing communities, this leads us to ask whether or not the pieces of information shared within these communities differ from what is relevant outside these communities. Analogous to the analysis from Figure IV.17, I opted to count the number of links to each domain (excluding Facebook), but separately for each of the five biggest communities in terms of AAS-groups. To reduce the amount of work and exclude rarely appearing domains, I used only the top ten domains in order of the frequency of their links, and hand-coded each domain to one of three categories “local/regional news website”, “national news website”, and “platform/other” as a residual category. As we have seen earlier, except for links to the YouTube platform, the information ecology of AAS-consists mainly of news websites, which is why we can focus on the dichotomy of regional versus national news. Firstly, it was striking that the regional news I identified within each community were indeed focused on the region where most of each community's groups were located. Secondly, as Table IV.12 illustrates, all of the top five communities show a higher fraction of regional news than the overall network.

Table IV.12 Fraction of links to regional news sources in different communities

Community	C1	C2	C3	C4	C5	Network
Fraction of links to regional news	.10	.18	.53	.43	.25	.08

In cases where the community is geographically more dispersed, like C1, the fraction is .10, while geographically more confined communities like C2 (Brandenburg), C3 (Berlin-Brandenburg), C4 (Southeastern Brandenburg), and C5 (mostly Baden-Württemberg) all show higher fractions of links to their respective regional news. We might speculate that these numbers are even higher, considering that some national papers like the tabloid "Bild" have regional sections or that YouTube channels might also have a regional focus. Due to the constraints of this thesis I focused the analysis only on domains, which do not allow for a more fine-grained classification. In any case, it is likely that a more fine-grained approach will even increase the fraction of localized content. The key information however is that while national news and the stories therein form an important part of the flow of information through the overall network, it is regional news and their localized stories that may explain the formation of localized cohesive subgroups in the information sharing network. The implications of this are twofold: neither are we likely to witness a NIMBY[65]-phenomenon, in which AAS-groups care about the opposition to asylum-shelters in their local setting but are oblivious to being part of a greater protest

[65] Acronym for Not In My Back Yard

phenomenon, nor do the affordances of social media lead to a sharing behavior that neglects the importance of localized content. The role of the regional brokers in that logic however remains unclear. In the two cases C2 and C4, where we could clearly identify such powerful actors, their removal from the analysis would lead to values of .17 and .67 in Table IV.12, meaning only in one case did the broker clearly share more national than regional news. Thus, from the lack of cases we cannot clearly say whether or not they serve as a bridge between more national and more regional content. What we can more confidently conclude from that exercise is that the sharing of regional news content can serve as an important mechanism for the formation of localized communities in the information sharing network. Removing the identified domains of the most linked regional news and constructing an information sharing network without pieces of information from this domain is a simple way to test their function. Indeed, subjecting such an "treated" network to the same analyses as the original information sharing network reveals a less clear-cut community (Q=.30) and a far less localized community structure.[66]

Thus, to sum up the results of the investigation of this type of tie, we can conclude that the information sharing networks shows a clear-cut localized community structure, driven by the sharing of more respectively local pieces of information within than across communities. In addition, the communities exhibit different internal structures. In some cases, despite high cohesion within communities and thus low centralization tendencies, we could nonetheless identify powerful brokers whose

[66] Although we may argue that a more thorough undertaking of this kind would require the identification and exclusion of all regional links, not only the most shared ones. However, given limited resources, this was not feasible.

connections span across different communities. We could also see that many of the groups which are central in terms of degree and betweenness were already prominent in either popularity or outreach in the recognition network. However, while information sharing is clearly an important part of resource exchanges, some researchers have argued that collaborative collection action is a more rigid criterion to asses interorganizational networks (Saunders 2007). Therefore, in the following passage we will turn attention toward AAS-group's co-involvement in (offline) protest events as an additional and final way to operationalize resource exchanges.

Co-mobilization

In his application of the MoC framework, Diani (2015) analyses the joint involvement of organizations in events both as a *network of organizations* being connected through events and as a *network of events* being connected through organizations. Public events from a collective action perspective serve to "*bring two or more people together to realize a common purpose or specific claim*" (Sampson et al. 2006:675). In that sense, Sampson and colleagues claim that "*movements and related protest events are not just aggregations of individual participants; rather, they are social products born of complex interactive dynamics played out within established social settings*" (2006:678). We can clearly see how that understanding of events resonates well with a relational perspective to collective action and how studying these dynamics with the means of SNA lends itself well to foster our understanding of the interplay between groups and events. It must be noted however that events form a broad category, that may span from peaceful neighborhood meeting to disruptive protests like sit-ins or squatting. Therefore, Sampson and colleagues (2006) distinguish between "civic", "protest", and "hybrid" events, while Diani (2015) operationalizes "civic" and "protest" events to study joint involvement in either of the two. While it is meaningful to distinguish theoretically and empirically between the participation in a charity event and a violent street confrontation, the inspection of events in this chapter will illustrate that in the case of AAS-groups, the events are overwhelmingly demonstrations and as such of the *protest* type - given the *oppositional* nature of AAS-groups, this might not come as much of a surprise. As Diani argues, public events do by no means "exhaust" the experience of movements in particular, but they "*offer movement actors their best opportunity to attract wider* *attention, making their voices heard, or challenging everyday life routines*" (2015: 120). Thus, co-participation in or more precisely co-mobilization for public events is a visible display of joint claims and can both lead to fostering solidarity and collective identity. As such, co-mobilization ties might as well be treated as the boundary defining type. However, they require the strategic choice to devote limited resources of attention and leverage of mobilization potential by each group. It is precisely the latter aspect that invokes a notion of co-mobilization as an "*instrumental collaborative tie*" (Simpson 2015:49, cf Saunders 2007) and thus I opted to treat the joint mobilization for a public event by two or more AAS-groups as a type of resource exchange.

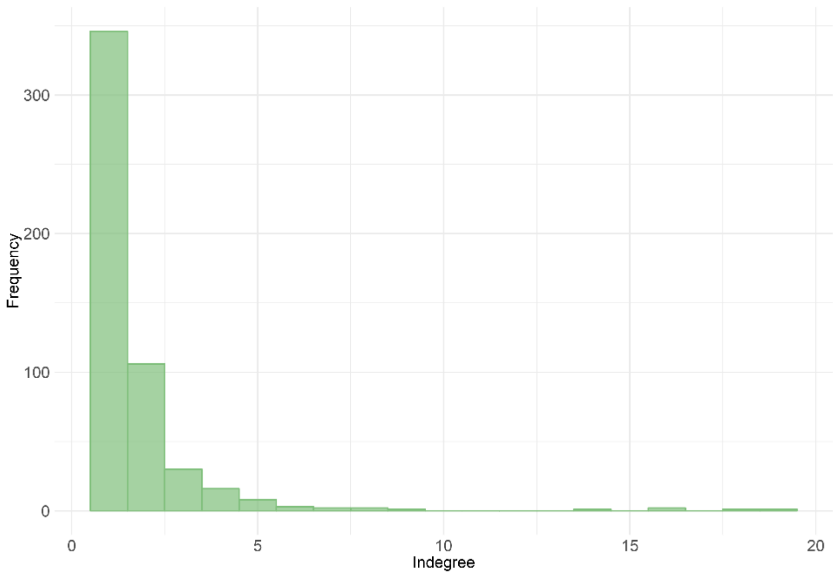
The data to operationalize mobilization for events can be taken from the Facebook dataset on the 185 AAS-groups introduced in chapter III. It must be noted that Facebook offers the possibility to create, share, and claim to attend real live events, such as parties, meetings, or demonstrations. The creators of a post (thus usually administrators) can select the category of an *event*, enabling certain functions like confirming attendance before and after the event, calendar entries, additional discussions, etc. Thus, to increase visibility and participation, it makes sense to assume that if AAS-groups are interested in publicly promoting an event, they will use the *event* category of Facebook's post typology. Therefore, we will investigate exactly these types of posts as events in this chapter. Table IV.13 sums up the collected event data: 128 of all 185 AAS-groups mobilized 957 times for 519 unique events. Excluding double postings of the same event within the same AAS-group, we can count 892 unique group-event pairs. Thus, on average each group mobilized for 6.97 events. As the lower median and the range suggest, few groups stand out by being more active, with a maximum of up to 51 events being promoted by a single group.

Table IV.13 Events in the AAS-data

Events	
Total Links	957
Unique links	892
Unique events	519
Per group mean	6.97
Per group median	3.5
Per group range	[1 - 51]

Before we begin the analysis of the network of co-mobilization by AAS-groups, we will briefly shed a light on the events themselves and explore what we can learn to foster our understanding of AAS-protests in terms of the issues, the locations, and the relative importance of these events. A first step in doing so, is to simply look which events drew the most attention in terms of receiving mobilization calls from different AAS-groups. In a bipartite, directed network between groups and events, this would correspond to an event's indegree.

Figure IV.23 Histogram of indegree of 519 events in a bipartite group-event network



From Figure IV.23, which illustrates exactly this measure, we can see that while most events are mobilized for only once, there are nonetheless 173 events that receive mobilization calls from at least two different AAS-groups, i.e. they have an indegree above one. The histogram also shows that most of these events do not receive more than nine different mobilization calls – with a few exceptional events that drew the attention of up to 19 different groups. For an in-depth analysis of the characteristics of events that draw many AAS-groups' attention, I inspected the Facebook pages of all 38 events that received calls from more than three groups[67]. In eight cases, it was not possible to retrieve data anymore, as the pages were deleted. The data that is publicly visible on an events page includes the title, a description text, the location and time, a link to the initiator's page, and in some cases an attendance count. Of the 30 remaining events, all were street protest events, either in the form of demonstrations or of vigils at the construction sites of asylum shelters. Thus, when speaking of events in the case of AAS-groups, it is likely that we exclusively mean *protest* events, as opposed to civic events (Sampson et al. 2006). In addition, 28 of the 30 events took place in the former GDR or in Berlin, with only two events held in South-Western Germany. Regional foci clearly lie in the regions of Brandenburg and Saxony, where we could also locate many AAS-groups. A look at the initiators of these 30 events reveals than in 14 cases, events were initiated by AAS-groups themselves. On the one hand, we need to be careful, as initiating an event on Facebook does not necessarily mean organizing it on street level – it merely means to be the one who enters the event into Facebook's system. On the other hand, given the ubiquity of Facebook, it seems reasonably

[67] Surely this number is arbitrary to some extent, but it should allow the inclusion of the most important events while at the same remaining feasible in terms of the effort required.

unlikely that any other group of activists who organizes a demonstration would not also be the one who posts it. In the cases of events organized by the Berlin and Leipzig chapters of PEGIDA, which can also be found among the 30 inspected events, it was clearly the organizers themselves who also initiated the event on Facebook. Therefore, we can assume that AAS-groups do not only join in on existing events but apparently, in some cases, invest the resources to stage own events. A qualitative and non-systematic look at the titles and descriptions of the events further reveals that all of them deal with various aspects of migration. In some cases, the topic is the immediate opposition to an asylum-shelter, expressed in the title "*Silence means acceptance - We are not silent! Spremberg says no to the Asylum shelter!*"[68]. In other cases, the topic is violence and crime perpetrated by foreigners, expressed in the title "*German victims, foreign Perpetrators*"[69], or "*Us against violence*"[70], or "*Security instead of fear! Right to the future – courage for resistance*"[71]. Other topics of these events include the call for remigration, the closing of German borders, the resignation of the German government, or Germany's withdrawal from the European Union and the North Atlantic Treaty Organization, calling for an alliance with Russia. In addition, the target group addressed by these calls is generally the "*German citizen*" or the "*German patriot*", while the initiators often speak of themselves as "*concerned citizens*", "*citizen initiatives*" or "*citizen movements*". This corresponds to the identified self-reflection of AAS-groups in the chapter on content analysis, where the civil and civic nature of the self, the concerns, and the tactics was frequently highlighted. Also, many

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[68] Original German: "Schweigen heißt zustimmen - Wir schweigen nicht! Spremberg sagt Nein zum Asylheim!"
[69] Original German: "Deutsche Opfer Fremde Täter"
[70] Original German: "Wir gegen Gewalt"
[71] Original German: "Sicherheit statt Angst! Recht auf Zukunft - Mut zum Widerstand!"

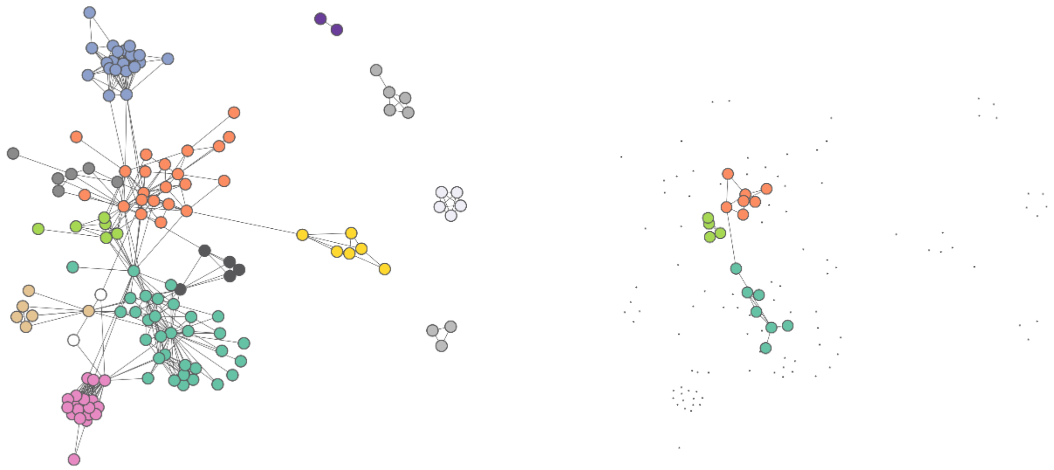
demonstration descriptions include calls to abstain from violence and oftentimes the initiators seem well versed in the rules and laws required for a demonstration in Germany (e.g.: regarding flags, glass bottles, dogs, tattoos and symbols). We may thus speculate that at least those who organize the events do possess some experience in protest.

Even from this brief inspection, we can conclude numerous things. *Firstly*, in many instances the issues promoted via events are in line with the topics discussed within AAS-groups, analyzed in a previous chapter of this dissertation. *Secondly*, while some events revolve around the opposition against a specific asylum shelter, many other events (at least of the sample) deal with various concerns, yet all regarding migration. Thus, AAS-groups do not remain confined to a single issue (asylum-shelters) but also express to be part of a wider collective of anti-immigration groups. *Thirdly*, despite the civic façade, these issues and the perspectives taken on them can clearly be categorized as right-wing. *Fourthly*, AAS-groups do not only join in on other protest phenomena they regard as worthwhile, but also very likely possess the experience and hence organizational resources to stage own protest events. And *fifthly*, the geographic scope of the events promoted clearly overlaps that of the main activity of AAS-groups, as explored in an earlier chapter.

Before we turn attention toward a network of co-mobilization among AAS-groups, I will briefly discuss how events are related to another by being mobilized or. This is analogous to the approach taken in Diani (2015), who analyzed the "*duality*" of events and organizations. While the focus of this work is on interorganizational networks, we will not dive too deep into an analysis of this network, but rather add a perspective on the way events are interrelated to the debate above. The left side of

Figure IV.24 is a visualization of the network of events that are connected by at least two AAS-groups. We can both see that the network is partitioned into one giant and four smaller components. Node colors additionally represent the results of a community detection using the Informap algorithm. A visual inspection confirms what the modularity score of Q=.73 already indicates: There are clear cohesive subgroups of events that are densely interconnected among each other, but loosely (or not at all) connected to the rest. The right side of the figure highlights events and their connections only when they are connected by at least four different AAS-groups. We can see that this excludes all but 18 events, and that while the smaller components have disappeared, the giant component is partitioned into two.

Figure IV.24 Components and communities in the network of events connected by at least two (left) and at least four (right) AAS-groups



To offer a substantial interpretation of that split we may assume that there are certain key events that draw the attention of more AAS-groups than other events, leading groups to use their resources and direct attention of their members towards these events regarded as important. And apparently, different events perform that function for different sets of groups, as even though the sets of events in the right of

Figure IV.24 are promoted by at least four groups, only connected events are promoted by the same groups. If we take a closer look at these 18 events and their partition into components and communities, some clear commonalities arise. First of all, these events all belong to the ones discussed above. This means the events that overall received many mobilization calls are also the ones that are interconnected by receiving calls from the same set of groups. A closer inspection reveals that the four events of the smaller component, that are colored in green in Figure IV.24, all took place in Eastern Brandenburg and were all initiated by (three different) AAS-groups. The 14 events of the larger component are partitioned into two different communities, each of size seven. Remarkably, all but one event of the turquoise community took place in Saxony and all events of the orange community took place in Berlin or nearby Brandenburg. The only event bridging the two communities is exactly the non-Saxon one and it was held in Berlin. The initiator of this event was the local chapter of PEGIDA, called BÄRGIDA. While we must not overly generalize the results from this sample, the inspection of these key events nonetheless tells us that there is a clear clustering of events, corresponding to geographic proximity. In other words, events that are spatially close receive attention from the same set of groups. In addition, the one event performing a bridging function was one initiated by a chapter of the prominent right-wing PEGIDA phenomenon. Thus, we may speculate that a general adherence to the universe of German right-wing groups might serve to bridge the more localized and specific protest events against asylum-shelters. As both matrices resulting from the one-mode projections of a group-event network are related, we might thus expect clustering tendencies and localized patterns also in the co-mobilization network of AAS-groups. To following sections will investigate this network in more detail and compare it to the networks that resulted from other types of resource exchanges.

Network Construction

As the above discussion of events has already shown, we will investigate a one-mode projection of the bipartite group-event network. Analogous to events and to the information-sharing network, transposing and multiplying matrices yields a 128*128 symmetric affiliation matrix in which the cell values contain the number of different events two AAS-groups have promoted. All 57 groups who did not mobilize for a single event were nonetheless added to the network as isolates. This step is warranted, as they surely had the chance to do so but voluntary opted out. The benefits are that the network thus remains stable in size and measures are comparable.

Table IV.14 Properties of the co-mobilization network before and after edge reduction

Network Properties	Before Reduction	After Reduction
Nodes	185	185
Isolates	57	148
Edges	802	38
Density	.047	.002
Range of edge weights	[1 – 17]	[3-17]
Mean edge weight	1.50	5.29
Median edge weight	1	4

Unlike the information sharing network, edge weights remain on a comparable scale. Nonetheless, to account for the strong variation in group activity, I proceeded analogous to the backbone approach outlined in the information sharing network and used α=.1 as a cut-off value to exclude edges. As Borgatti et. al (2013) argue, not controlling for variation in group activity results in the actual *pattern* of co-mobilization, while controlling for it reveals also the *underlying tendencies* of co-mobilization. However, in the empirical data at hand, only two edges of a weight higher than five get excluded with the alpha cutoff, thus making the results very similar to an analysis of only strong edges in absolute terms. The results of this process are summarized in Table IV.14. It shows that under this stricter criterion, only 37 groups remain connected by 38 edges with an average weight of 5.29 events they co-mobilized for. Thus, similar to the information sharing network, the reduced backbone of this network will allow to more clearly highlight the structural patterns in the practice of co-mobilization for protest events among AAS-groups.

Graph

While some properties of the network have been introduced above, Table IV.15 includes additional measures and a comparative perspective on all three networks of resource exchange among AAS-groups.

Table IV.15 Structural properties of the recognition, information sharing, and co-mobilization networks

Measure	Recognition	Information Sharing	Co-mobilization
Directed	Yes	No	No
Weighted	No	Yes	Yes
Edges	579	941	38
Range of edge weights	n.a.	[3 – 3,827]	[3 – 17]
Mean edge weight	n.a.	39.9	5.29
Total edge weight	n.a.	37,542	201
Density	.017	.055	.002
Reciprocity	.18	n.a.	n.a.
Isolates	29	26	148
Fraction of Isolates	.16	.14	.80
Components (isolates excluded) weak/strong	1/3	1	6
Maximum Component Size weak/strong	156/53	159/n.a.	15/n.a.
Average Path Length	3.67	2.42	2.29
Connectedness weak/strong	.71/.08	.74	.001
Centralization (in-degree)	.12	.46	.04
Centralization (out-degree)	.29	.46	.04
Transitivity	.20	.32	.24

From these measures we can deduce that co-mobilization is a more exclusive practice than recognition or information sharing, as both the groups and the exchanges are fewer than in other networks, as only .2 per cent of all possible ties between groups are realized. Of course, protest events are not entirely comparable to pieces of information, as there is fewer “supply” for AAS-groups to choose from, and initiating own events requires considerable organizational resources. On the other hand, the cost of simply informing about an event consumes almost no time and effort – the fact that we witness only 128 groups doing so at all and even fewer doing it for the same event, may be interpreted as groups taking events seriously. This means there is likely a careful selection of events to promote and a realistic anticipation of administrators and members to actually attend the event. As such, the ties in this network are far from meaningless feel-good “clicktivism” but instead can serve as a good indicator for strong collaborative ties among AAS-groups.

As the fragmentation of the event network has suggested, also the co-mobilization network is partitioned into six different components, the largest comprised of 15 groups. This explains the low connectivity score, as the high number of isolates and the fragmentation mean that only very few pairs of nodes can reach each other. The same is true for a centralization score that is hard to interpret given the different components and the many nodes of degree zero. Where nodes are connected however, their tendency towards transitivity is comparable to the other two networks, ranging in the middle with a score of .24. The shorter average path length must also be handled with care, as many paths are nonexistent, and several small components of course mean smaller maximum lengths. Therefore, the important takeaway from an inspection of the entire graph is its small size and its partition into different components. Before we take a look at the latter, we will focus attention on the identification of key nodes within this network.

Nodes

As we have already learned, 148 nodes are isolated, meaning they are not connected to each other by a single event. This does not mean they do not mobilize for events at all – that only applies to 57 groups – but they do not mobilize for the same events as others, thus not investing resources in the same objectives and not having to potential to meet in the streets and forge deeper interorganizational or interpersonal alliances offline. Nonetheless, among the 37 groups of the co-mobilization backbone, we may discover some groups to play a more central role than others. Unlike the histograms in previous chapters, I use Table IV.16 to illustrate the distribution of degree centrality across nodes, as the limited range suits this simpler form of data presentation.

Table IV.16 Degree distribution in the co-mobilization network

Degree	1	2	3	4	5	6	7
Groups	18	12	2	2	-	1	2

From the table we can read that most groups are only connected to one or two other groups, while seven groups hold connections to three or more other groups, with a maximum of seven. The five groups with the highest degrees are, in descending order, BB17, BB31, SN06, SN33, SN01. As we can see, two of these are based in Brandenburg and three are based in Saxony. Additionally, three of them are well known acquaintances by now: BB31 has shown to be very popular in the recognition network as well as highly central in information sharing, whereas SN06 and SN33 have shown to be outreaching in the recognition network as well as highly central in information sharing. Nonetheless, this relationship seems far from deterministic, as with BB17 and SN01 we can identify two very central nodes in terms of co-mobilization that have not featured prominently in the other two networks.

Figure IV.25 Components in the co-mobilization network

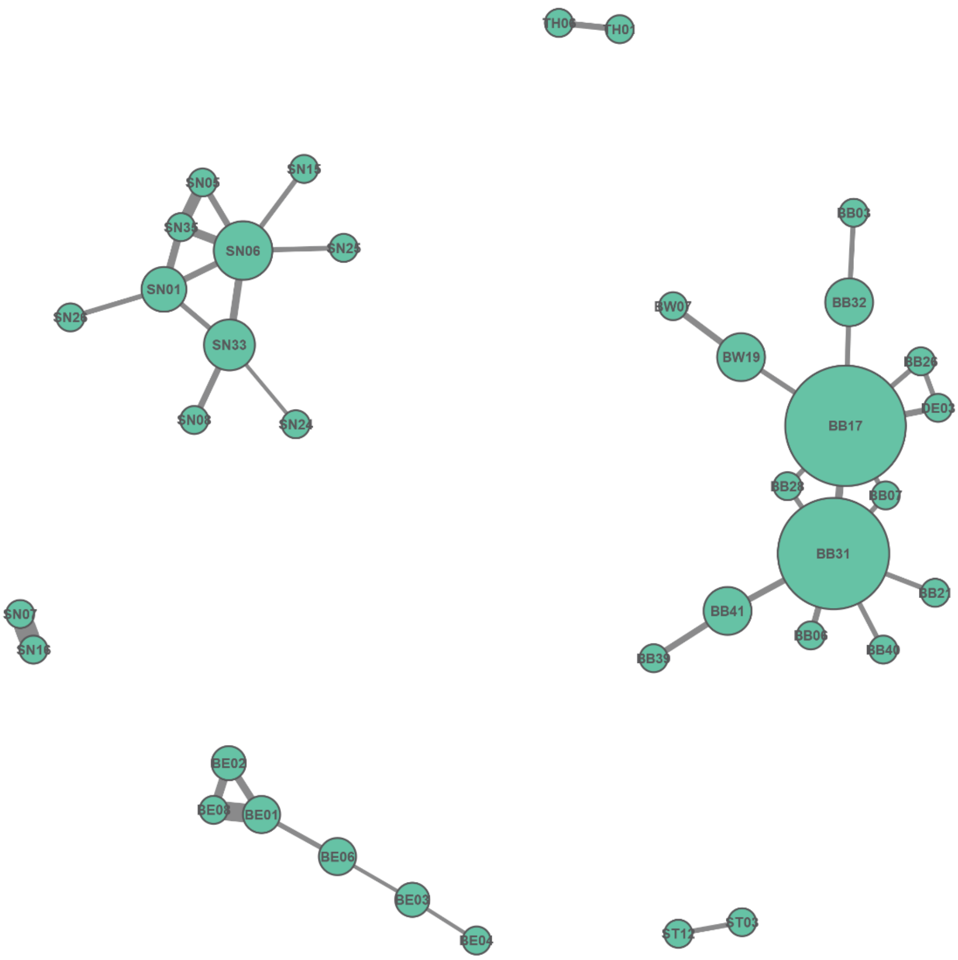


Figure IV.25 illustrates the six components of non-isolated nodes in the co-mobilization network along with some properties of both the AAS-groups and their connections: Node size in the network corresponds to a groups betweenness centrality while the thickness of an edge corresponds to its weight, i.e. the strength of relationship. What we can see is that the most central nodes in terms of degree play very different roles when we take into account how their connections are configured and how strong these connections are. Firstly, we can see that none of the lines connecting BB31 and BB17 are very thick, meaning while they both hold seven connections, the average weight of each tie, i.e. the weighted degree centrality of these nodes is 4.57 (BB31) and 4.43 (BB17) and thus not much above the minimal edge weight of the network, which is 3.00. However, they each connect different groups to each other, that would otherwise remain unconnected to the component, meaning they fill structural holes in the network and may play the role of brokers of gatekeepers, leading to a high betweenness centrality. Removing BB31 and BB17 would result in either isolates or at maximum pairs of nodes, as the nodes connected to these two groups are rarely interconnected themselves. It means that in such a configuration these groups highly depend on the two powerful actors. This is slightly different for the Saxon groups, as SN06 and SN33 hold two and SN01 holds one non-redundant connection, meaning that removing any single one of these groups would leave less groups unconnected than in the Brandenburg case. This is expressed in their lower betweenness centrality scores, which must however be handled with care, as a smaller component size by definition limits the number of paths, and therefor shortest paths, that may flow through any node. When taking weights into account, the weighted degree centrality for SN06, SN01, and SN33 is 5.17, 4.75, and 4.5 respectively. Thus, we can see that on average, at least SN33 and SN01 hold slightly stronger connections than the central counterparts in Brandenburg. Nonetheless, none of these three groups are adjacent to the strongest edges in the network, as having many connections seems to come at the cost of having weaker connections. In fact, the highest weighted degree centrality is shared among SN07 and SN16 (lower-left corner of Fig. 4.26), that hold only one connection, but the strongest of the entire network, with 17 acts of co-mobilization (thus leading to a weighted degree centrality of 17 for both). BE08 and BE01 of the Berlin component at the bottom of the figure hold weighted degree centrality values of 11 and 8.34, being adjacent to two, respectively three other groups, but sharing the second-strongest tie in the network, with a value of 15 events. To sum up, while many groups are weakly connected in terms of the number of connections and the strength of these connections, we can also observe groups that share strong connections, but mostly hold only very few of them, and groups that hold comparably many connections, but rarely any strong ones. This also influences the structure of the different components, which shall be discussed a bit more in-depth in the following section.

Communities

While I label this section "communities", in line with the structure of previous and following chapters, it would more accurately be called "components", as the partition of the network is already given by these. It is worth noting however, that the infomap-algorithm further breaks up the Brandenburg and the Berlin community, due to the structure of the former and the distribution of weights in the latter. Nonetheless, the components offer a clear structure that does not require additional algorithms to be more interpretable.

Table IV.17 Structural properties of all seven components in the co-mobilization network

Measure	C1	C2	C3	C4	C5	C6
Nodes (fraction of network)	15 (.41)	10 (.27)	6 (.16)	2 (.05)	2 (.05)	2 (.05)
Internal Edges (fraction of network)	17 (.45)	12 (.32)	6 (.16)	1 (.03)	1 (.03)	1 (.03)
Total weight of internal edges (fraction of network)	75 (.37)	62 (.31)	38 (.19)	17 (.08)	5 (.02)	4 (.02)
Mean weight of internal edges	4.41	5.17	6.34	17	5	4
Density	.16	.27	.4	1	1	1
Average Path Length	2.47	2.02	2.07	1	1	1
Centralization (degree)	.34	.4	.2	0	0	0
Centralization (betweenness)	.59	.49	.4	n.a.	n.a.	n.a.
Transitivity	.18	.29	.42	n.a.	n.a.	n.a.
Average edge length in km	154	45	8	8	8	15

Table IV.17 sums up some of the properties of these components, although we must note that results for components of size two are hardly interpretable. C1, that consists of 12 groups from Brandenburg, two groups from Baden-Württemberg, and one Germany-wide group has been discussed in light of its two central groups already. This structure, as visualized in Figure IV.25, is well reflected in the overall highest betweenness centralization score of all components and a relatively low transitivity. While 45 per cent of all edges fall into this component, only 37 per cent of the total edge weight do so, meaning on average, connections among the groups C1 are slightly weaker than in most other components, reaching only 4.41 joint events per tie. C2, the first all-Saxon component has a slightly higher average weight of 5.17 events per tie and is also denser (.27) than C1 (.16), albeit slightly more degree centralized due to the role of SN06 and SN33. The Berlin component C3 realized 40 per cent of all possible ties and as we have seen, one of the heaviest edges in the network lies within this component, driving the average edge weight up to 6.34. C4 to C6 are included in table for the sake of completeness, as many network metrics make little sense between only two groups. What is truly remarkable and should be the main conclusion of discussion of communities within this network is that with the exception of C1, all components are comprised of geographically close groups from the same German Land. In the case of C2 and C4, all groups are from Saxony, in C3 all groups are from Berlin, in C5 both groups are from Thuringia and in C6 both groups are from Saxony-Anhalt. This mirrors the spatial distribution of the event-event projection, where we have seen that events that are co-mobilized for are generally close to each other geographically. As the network and its partitions are already visualized in Figure IV.25

I will not provide a spatial mapping at this point, but refer the reader to Appendix Figure A.8. Here it suffices to say that even though the components already follow a spatial separation, within C1 and C2, the central groups BB17, BB31, SN33, and SN06 act as even more localized hubs that connect geographically close groups to the rest of the component. Thus, the neat separation of AAS-groups into spatially close components of co-mobilization supports the implication of the event-network that not only events are close together, but also groups who mobilize for these events are from the same area. As the costs and organizational effort to participate in offline events in other areas are high, this geographic fragmentation seems understandable. On the other hand, as we have discussed earlier, informing about events in distant areas in the form of posting a Facebook event, consumes little time and effort. Therefore, we can again find support for the assumption that only events are posted on a page, if the real-life participation of users seems realistic and is anticipated. Thus, some groups use Facebook for clearly more than mere low-cost networking but take it serious as an alternative or addition to offline mobilization efforts. However, we must bear in mind that even though many AAS-groups do mobilize for (protest) events, only a minority of them is connected in strong collaborative ties of co-mobilization in the backbone of this network. Before we turn our attention toward the question of how this and the other two networks of resource exchange combine to a typology of Modes of Coordination of collective action, we must first discuss the second dimension of the framework: boundary definition. Therefore, in the following section I will provide an operationalization and empirical investigation of the networks that indicate stronger or weaker connections among AAS-groups in terms of boundary definition.

Boundary Definition

Co-membership

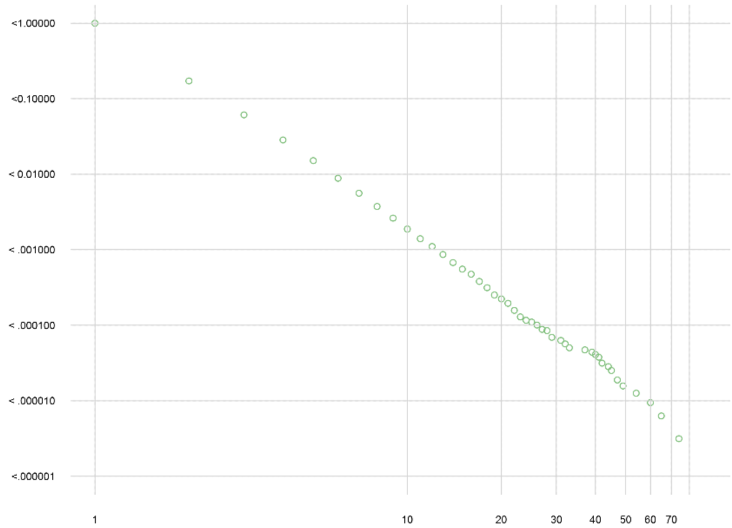
The theoretical reasoning behind co- or overlapping membership of activists has been debated in chapter II of this thesis, but we can briefly review the logic here. Simply put, we may understand the role of boundaries between AAS-group such that "*symbolic boundaries are […] demarcations among people or objects that help to make sense of the world around us*" (Wang, Piazza, and Soule 2018:168). In that understanding, boundaries may be functional in distinguishing in- and outgroups, fostering solidarity, and forming collective identity. Especially for informal organizations, boundaries may well be fluid and if perceived in terms of memberships, i.e. who belongs to an organization and who does not, boundaries may not always be clear and visible. In the MoC framework, that defines collective action phenomena as different configurations of interorganizational networks, the investigation of "*members' multiple involvements*" thus allows to study "*flows of communication, identity and solidarity*" (Diani 2009:65). As such, we may understand multiple membership of individuals in organization as a form of "*boundary-spanning*" (Wang et al. 2018) that can help forge the bonds of deeper solidarity versus a mere instrumental collaboration between organizations. Simply put, "*multiple involvements provide an indicator, no matter how rough, of whether core activists perceive two organizations as compatible and close to the point of sharing their individual commitments between them*" (Diani 2015:83). This perspective follows a sociological tradition rooted in Simmel's (2013) understanding of intersecting social circles, which has been prominently developed into a "*membership network analysis*" by Ronald Breiger (1974). For voluntary, informal, and partial organizations such as AAS-groups, one key question arises before we may speak of a network of co-membership, namely that of membership at all. Surely, there is no way to ascribe the category of formal membership to any affiliation between individual and organization in this case. Nonetheless, we can look at empirical data to trace users' behavior and thus see that involvement of users with organizations is generally limited to a single or very few groups and consists of the repeated interactions that may well serve as a proxy for membership in this case. To illustrate this, we will make use of the Facebook dataset on AAS-groups and look at the distribution of all 2,345,774 activities by 317,977 unique users over the 185 AAS-groups. As the data has a unique identifier for the user behind any activity, we can investigate patterns in user-group interactions and trace evidence for a membership-like structure. Table IV.18 briefly illustrates the relationship between these numbers.

Table IV.18 Activity averages for groups and users

Average activities per group	Average activities per user	Average unique users per group
12,679	7.38	2,248

The table tells us that on average, each group has 12,679 activities, while on average each user was active 7.38 times in the data observed. In addition, on average, we can find 2,248 unique users in every group, regardless of the number of activities for each user. This already shows that there must be overlaps, as allocating each user to one and only one group would produce an average of 1,718. This means that while there must be an overlap of users between groups, an overwhelming majority of users remains active on one or only a handful of pages. Indeed, Figure IV.26 provides insights into user behavior in the form of a CCDF-plot. On a log-log scale, we can see that the probability for each user to be active in more than one group, drops steeply for each increase in unit on the x axis (i.e. additional group). This means it is empirically more and more unlikely to find users that are active in more groups. In fact, 17 per cent of users were active in more than one group and less than one per cent of users were active in more than five different groups.

Figure IV.26 Empirical complementary cumulative distribution function (CCDF) of the number of groups each of the 317,977 unique users was active on.



Thus, however unlikely in the distribution, these users do exist and as the plot shows, very few users spread their activity across many groups, with a maximum of 74 groups for a single user. Table IV.19 adds another perspective on this data that might need some explanation. The first column shows the average percentage of unique users of each group that were also shared with any other group. This means, that on average, each group shares 1.5 per cent of its users with any other groups. On average, the highest overlap of users with any other group is 22.5 per cent of a group's users.

Table IV.19 User sharing among groups

	Fraction of users shared per group	Average maximum fraction of shared users with any other group
Mean	.014	.225
SD	.013	.130

Substantially, this means that we do witness a behavior in which most users are repeatedly active in one and only one group, which is why we may assume this usership to resemble a form of membership in this informal, digital setting. For this reason, I will refer to this behavior as membership or co-membership in the following analysis. As the data shows, there is also a core of networkers which are individuals active in several different groups, meaning they can foster bonds of interpersonal exchange that we can aggregate to an interorganizational network of co-membership among AAS-groups. While we may want to know more about the characteristics of these users, whose networking activity forges bonds between groups, we will not go deeper into this. On the one hand, I want to avoid singling out individual users for privacy reasons. On the other hand, I did not collect any individual user information that could be used to do so. As the focus of our study lies on the group-level, I believe this to be the ethically correct and scientifically justified step. Therefore, we will now move on to a co-membership network among AAS-groups which will be the object of analysis in the section to follow.

Network Construction

Analogous to events and to pieces of information, the member-group network is a bipartite one, that will be reduced to its one-mode projection of groups. An important difference is that we can meaningfully interpret the values of the two-mode matrix, whereas I opted to dichotomize the matrix in the two earlier cases[72]. In other words, dichotomization in this case would discard information about the number of times, a

[72] The case that an event or a piece of information occurred multiple times in a single group was rare, and as it not necessarily beneficial to channeling attention, it might as well have happened by mistake. In any case, I opted for dichotomization, which facilitates the interpretation of the one-mode projection.

member was active in a given group. However, the approach of transposing and multiplying matrices will produce an edge weight for any pair of groups i and j, which would be the sum of all products of the number of activities of any member within the two groups. These would meaningfully weight stronger connections with higher weights but would be hard to interpret in substantial terms. While there are many methods to assign weights to the one-mode projection of a two-mode network, including some correlation-based methods, I opt for a naïve threshold approach in the weighs of the two-mode network and use the sum of overlaps for a one-mode projection. In other words, I dichotomized the member-group data, assigning a one to the relationship between a member and a group, if the member was active in that group at least four times, and assigning a zero otherwise[73]. The resulting one-mode projection thus reflects the number of more active members that are shared among groups. The properties of this network are shown in the left column of Table IV.20. Analogous to the data reduction techniques for the other one-mode projections, I applied the backbone approach with a cut-off value of α=.1, resulting in a network of co-membership with the properties shown in the right column of Table IV.20.

Table IV.20 Properties of the co-membership network before and after edge reduction

Network Properties	Before Reduction	After Reduction
Nodes	185	185
Isolates	2	49
Edges	4,058	589
Density	.237	.034
Range of edge weights	[1 – 678]	[3-678]
Mean edge weight	8.789	43.77
Median edge weight	2	19

[73] While this value might seem arbitrary, it does reflect the cut-off for the fourth quartile of edge weights in the two-mode network.

This shows that in the backbone of this network, 136 groups are connected by 589 edges, meaning that 3.4 per cent of all possible ties are realized in that network. On average, an edge has the weight 43.77, which is the number of more active members being shared by the two groups. Some exceptionally strong connections exist, with a maximum of 678, which also influences the median value of 19. Thus, we can be sure that a tie in the resulting network does not represent ephemeral activity but requires both a minimal activity of four for a user to be included and an overlap of three users to constitute a tie. This reduced backbone will hopefully allow to highlight the structural patterns of co-membership between AAS-groups

Graph

Some graph-level properties have already been introduced above, but Table IV.21 includes both additional measures and a comparative perspective on all four networks introduced so far.

Table IV.21 Structural properties of the recognition, information sharing, co-mobilization, and co-membership networks

Measure	Recognition	Information Sharing	Co-mobilization	Co-membership
Directed	Yes	No	No	No
Weighted	No	Yes	Yes	Yes
Edges	579	941	38	589
Range of edge weights	n.a.	[3 – 3,827]	[3 – 17]	[3 – 678]
Mean edge weight	n.a.	39.9	5.29	43.77
Total edge weight	n.a.	37,542	201	25,781
Density	.017	.055	.005	.035
Reciprocity	.18	n.a.	n.a.	n.a.
Isolates	29	26	148	47
Fraction of Isolates	.16	.14	.80	.26
Components (isolates excluded) weak/strong	1/3	1	6	3
Maximum Component Size weak/strong	156/53	159/n.a.	15/n.a.	131/n.a.

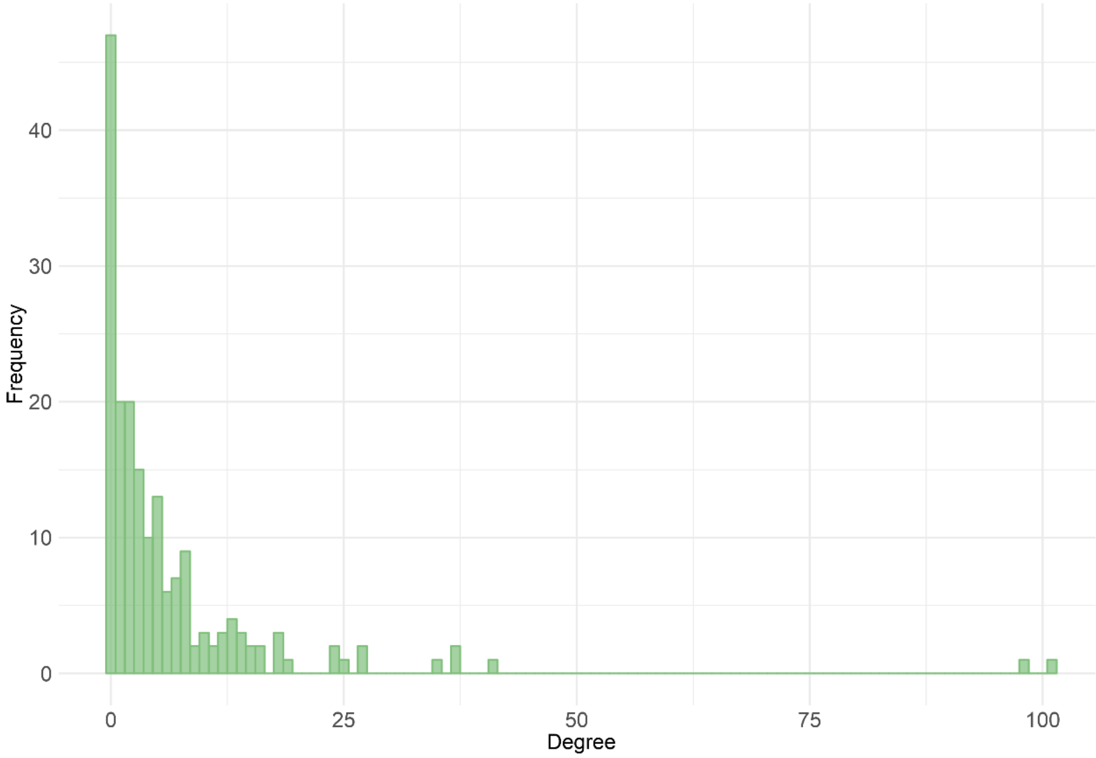
Average Path Length	3.67	2.42	2.29	2.14
Connectedness weak/strong	.71/.08	.74	.001	.51
Centralization (in-degree)	.12	.46	.04	.52
Centralization (out-degree)	.29	.46	.04	.52
Transitivity	.20	.32	.24	.25

The table informs us that for many of the metrics presented, the co-membership network occupies a middle ground between the co-mobilization network and the information sharing network. This is true for both the number of nodes and edges, the total weight, the number of isolates and of components, and the connectedness. What stands out is the highest value of centralization and the lowest average path length of all networks. These measures might mean that that we will likely discover that most nodes are connected to few very central nodes. These are probably connected to each other, so any node can, at least through an intermediary be reached quickly. The mechanism behind co-membership may be either members of less central groups "looking up" to more prominent groups or members of those central groups reaching out to widen their network. As we do not have directed data in this case, this must remain speculative. Nonetheless, the following inspection of central nodes and their role in the other networks, may allow for a more substantiated interpretation.

Nodes

A first interpretation of the graph-level centralization score can be helped by an inspection of Figure IV.27, which provides a histogram of the distribution of degree.

Figure IV.27 Histogram of degree distribution in the information sharing network



From this distribution we can read the already familiar phenomenon of many groups being connected to only one (20 groups) or two (also 20 groups) other groups and very few groups (two in this case) being each connected to around 100 groups. We have already witnessed a similar distribution in the case of information sharing, yet the discrepancy between the most central two and the third or fourth central groups is even larger here. The two most central AAS-groups in terms of degree are the Germany-wide DE03 with a value of 101 and BB31 with a value of 98. With values of 41, 37, 37, and 35 we may also call SN08, SN06, BE06, and SN33 central in this network. The exact pattern of BB31 and DE03 standing out above all other groups is familiar from the indegree distribution of the recognition network. In other words, the two most popular AAS-groups, both in terms of recognition within the network as well as in terms of user likes are also by far most central in the co-membership network. Given that both of these groups' administrators were uninterested in reaching out to other groups, we may speculate that the overlap in membership rather results from active members in other groups reaching out towards these two, and ending up being active there, rather than originating from there. Thus, we may reasonably assume a pull-mechanism at work to explain centrality in this network. Looking at these groups' roles in other networks, we can say that both BE06 and SN08 have not stood out prominently so far, meaning that centrality in this network is by no means determined by (for example) the proposed mechanism above. As of SN33 and SN06 however, we might remember that both are very active in terms of outreach in the recognition network and played central roles in both information sharing and co-mobilization networks. While the same is true for BB31, DE03 was remarkably absent from any highly central position in the other networks. All in all, we see that while some groups pop-up as central actors occasionally, a handful of groups seems to be central across the different networks. As the network is weighted, we can again compare weighted degree centralities, i.e. the average strength of each tie of a group. In this metric, the Berlin-based group BE01 stands out with an average overlap of 131.54 active users for each tie, followed by BE08 with a value of 87.48 and SN25 with a value of 86.94. The raw degree centrality scores of these groups are 13, 27, and 19, meaning that having many ties does again mean to have mostly weaker ties among them, i.e. a lower average weight. Before we move on to an analysis of communities and a visual inspection of the graph, we can briefly discuss betweenness centrality as a possible indicator of gatekeeping functions[74]. Here, the score of BB31 (3,805) exceeds that of DE03 (2,555), despite their similar degree centrality and a higher average tie strength

[74] However, it must be noted that this is a very rough measure, as for example a path's redundancy is not accounted for. For a debate see e.g. (Brandes et al. 2016; Fleming, King III, and Juda 2007).

(62.25) for DE03 than for BB31 (48.80). This means that even though DE03 holds both more and stronger connections than BB31, the latter may be in a more powerful position in terms of bridging parts on the network. This is best inspected visually, which we will do together with an analysis of communities in the following section.

Communities

I used the biggest component (nodes=131) for a community detection with the Infomap algorithm to identify cohesive subgroups, meaning sets of AAS-groups that have higher overlaps of active members among themselves than with the rest of the network. The community structure is not as neatly separated as in the information sharing and co-mobilization network, as the lower modularity value of Q=.23 illustrates[75]. Of the ten communities that the algorithm identified, Table IV.22 sums up the structural properties for all subgroups of at least seven members.

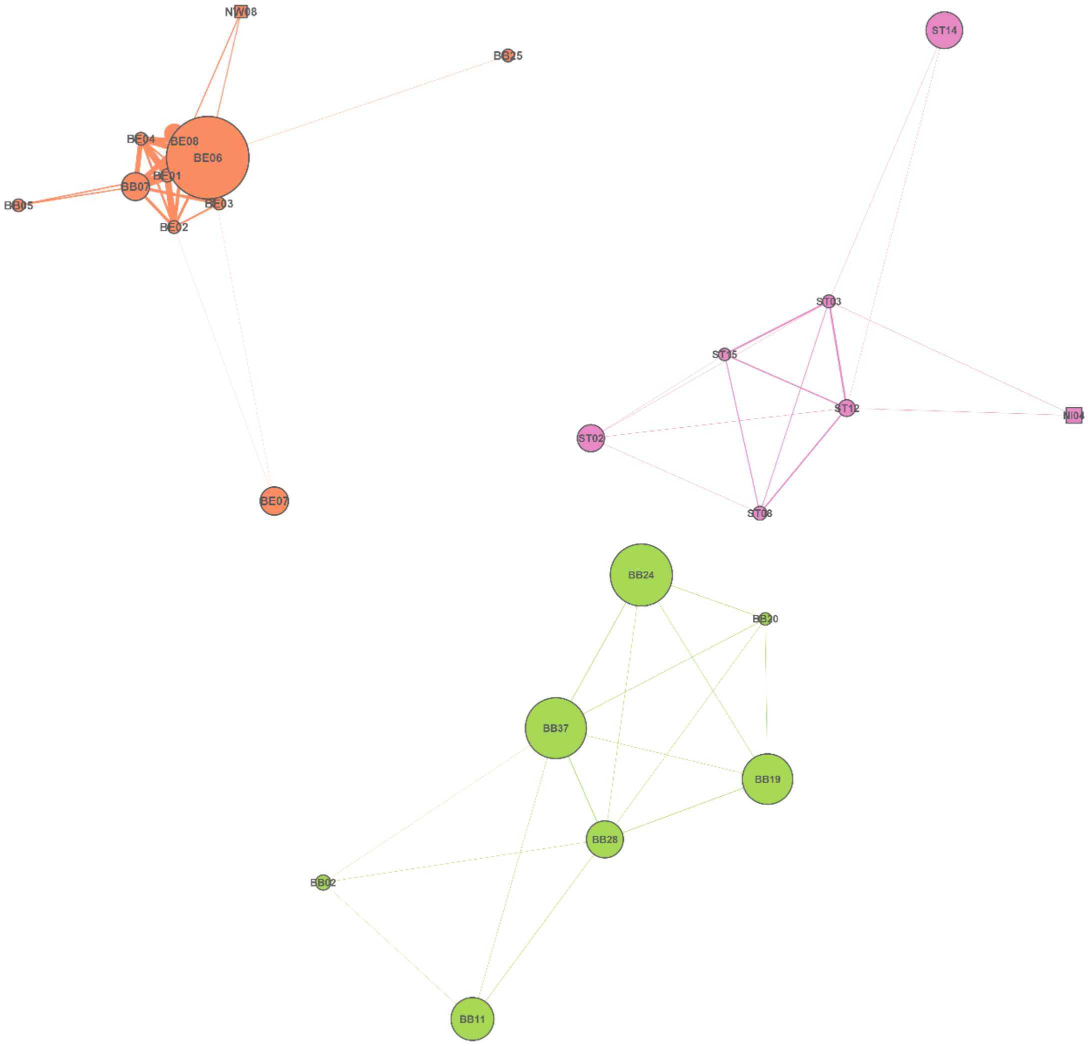
Table IV.22 Structural properties of communities of size > 6 in the co-membership network

Measure	C1	C2	C3	C4
Nodes (fraction of Component)	88 (.67)	11 (.08)	7 (.05)	7 (.05)
Internal Edges (fraction of Component)	379 (.64)	28 (.05)	14 (.02)	15 (.03)
Total weight of internal edges (fraction of Component)	17,170 (.67)	3,143 (.12)	257 (.01)	162 (.01)
Mean weight of internal edges	45.30	112.25	18.36	10.80
External Edges (fraction of Component)	108 (.18)	71 (.12)	12 (.02)	33 (.06)
Total weight of external edges (fraction of Component)	4,043 (.16)	3,554 (.14)	189 (.01)	537 (.02)
Mean weight of external edges	37.44	50.06	15.75	16.27
Density	.10	.51	.67	.71
Average Path Length	2.01	1.55	1.33	1.29
Centralization (degree)	.74	.39	.33	.29
Centralization (betweenness)	.38	.32	.19	.17
Transitivity	.28	.75	.72	.78
Average edge length in km	235	63	26	40

[75] This can only serve as a rough indicator, however, as the Infomap algorithm does not maximize modularity. Thus, we cannot infer a more separated or integrated structure from this score alone. Generally, modularity compares partitions of a network, not networks per se (Newman 2006).

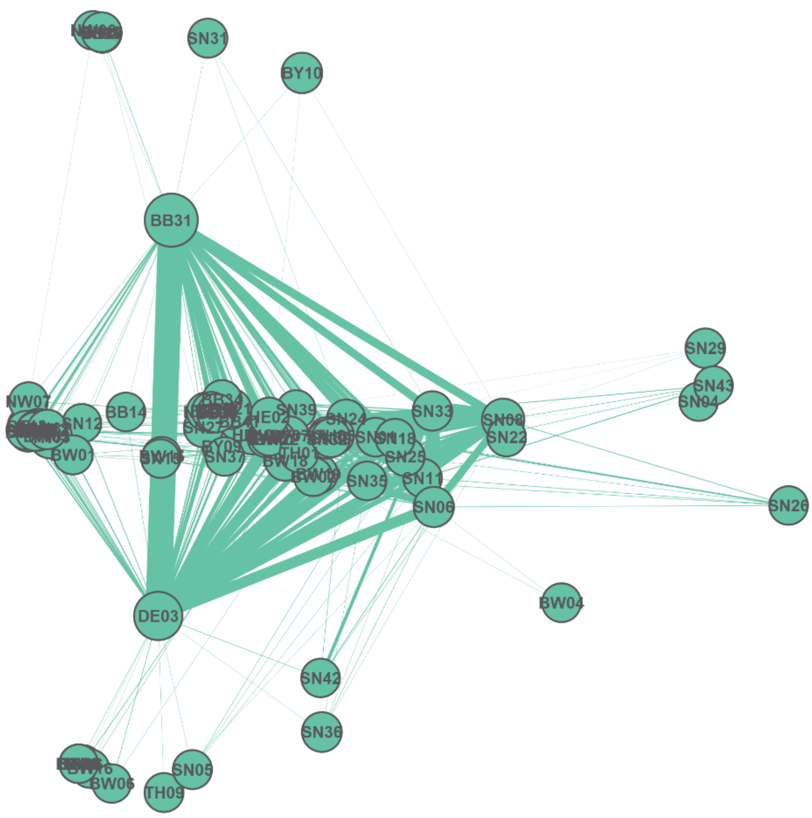
The table tells us that 67 per cent of all nodes of the component are grouped into one big community C1, with the smaller C2, C3, and C4 each having only 8 or 5 per cent of AAS-groups as members. In addition, we can see that also 67 per cent of the total edge weight lies in the 379 edges that connect the members of C1 to each other, meaning the average weight is very similar to the total networks average. While C3 and C4 are connected by weaker edges with mean weights of 18.36 and 10.80, C2 stands out with both in terms of the average weights that connect its members internally (112.25), and in terms of the weight of connections to other communities (50.06). Despite stronger internal ties, C2 remains well connected to the rest of the network through a total of 71 ties, which reflects that despite a higher cohesion within subgroups, the component in general is not as neatly separated as in some of the other networks we have discussed. While all communities are denser than the component (.07), the discrepancies in community size make the measure hard to compare, as in general bigger networks tend to have lower densities. Lower measures of centralization and higher density and transitivity characterize the smaller communities C2, C3, and C4. Figure IV.28 shows these three communities plotted separately. Node position is determined by the Fruchterman Reingold algorithm, that seeks to place well connected nodes in the center of the graph. Edge thickness corresponds to edge weight and circular nodes are those from the main geographic area of the community, while square nodes are from other regions Analogous to Figure IV.21, node size corresponds to each group’s betweenness centrality calculated for the entire network.

Figure IV.28 Communities C2, C3, and C4 (clockwise from top left) of the co-membership network



From the figure, we can read that geographic proximity seems to be important for the formation of community in this case, as each of the three graphs consists almost exclusively of groups from the same region, represented by circular nodes. A look at the average lengths of edges in these communities, measured in kilometers, shows that with 63 (C2), 26 (C3), and 40 (C4), edges in all three communities are significantly shorter than expected by chance. This means, a regional clustering is apparent in all three. In the case of C2, this is Berlin and surrounding Brandenburg, in the case of C3 it is Saxony-Anhalt, and in the case of C4, this is Brandenburg. Both C3 and C4 seem to be equally non-hierarchical when it comes to betweenness centrality, although in a different level. This means that within the community, no single groups hold specific gatekeeping power. For C1 however, we see that the group BE06, who was among the most central nodes of the entire network, seems to hold strong connections to some other community members, but also seems to monopolize the groups connections to the rest of the network. While these dynamics within smaller communities must not go unnoticed, what is more revealing in terms of co-membership is that the algorithm placed most of the central nodes we have discussed in one community, C1. To understand the whole network, we can thus focus attention on Figure IV.29, which visualizes C1 in a layout based on a multidimensional scaling of the adjacency matrix.

Figure IV.29 Community C1 in the co-mobilization network



Unlike Figure IV.28, node size does not have a meaning in this visualization, as the discrepancy in any centrality score between groups BB31, DE03, and the rest would render any such image unreadable. As edge thickness is however proportional to weight, we can see that by far the strongest overlap of active users (i.e. 678) is precisely between these two groups. Speaking in terms of equivalence, both groups are very similar: While both hold some ties to otherwise less connected groups, most of their connections are to the same set of groups. In some instances (to the left of the plot) these connections are weaker for both BB31 and DE03, and in some instances (to the right of the plot), the connections are stronger. Nonetheless, the many horizontal connections in this figure imply that despite their strength and despite the fact that these two groups lie most often on the shortest path between other groups, many of their connections are also redundant, as other groups would be able reach each other even in the absence of BB31 and DE03. Thus, the high centralization of the community and the overall network is driven by two actors who almost act as a single entity, given the strong overlap between them and their almost equal position in the community. Nonetheless, we must not forget the difference in network-wide betweenness centrality, where the much higher value for BB31 is explained by the fact, that this groups holds more connections outside of C1, thus brokering connections to the smaller communities.

Overall, the fact that two groups, who featured prominently and similarly in terms of popularity in the recognition network are so similarly positioned in the co-membership network, makes their different roles in information-sharing and co-mobilization even more intriguing. This may indicate that despite similar persons in both groups, the groups' functions in terms of mobilizing resources for collective action may still be very different. But before we look at how different combinations of networks play out to a mapping of actors in different Modes of Coordination, I want to close the investigation of networks with a last type of tie, namely topic overlap, which will serve to operationalize groups closeness in terms of issues and the framing of these issues.

Topic Overlap

This network utilizes results from the structural topic modelling exercised in the chapter on content analysis. The reasoning behind topic overlap as a form of boundary definition is that the data reflects interactions of sense-making among members of AAS-groups, their common negotiation of identity, and definition of "*collective us*" and "*collective them*". In terms of MoC, Diani argues that boundary definition is "*primarily associated with ideational elements, social representations, and framing processes*" (2015:16). As such, boundaries are defined as "*criteria that classify elements of social life in different groups and categories, while shaping the relations between those elements both within and between those groups*" (ibid.). In social movement theory, boundaries are often seen as key elements of collective identity (Melucci 1996; Touraine 1985), as Taylor and Whittier note: "*Boundary markers are, therefore, central to the formation of collective identity because they promote a heightened awareness of a group's commonalities and frame interaction between members of the in-group and the out-group*" (1992:176). In other words, the constant debate about who "we" are and who "they" are, and what traits and actions are ascribed to in- and out-groups is central in the formation of a collective identity, but much overlooked in studies of digitally mediated contention. Yet it remains a crucial issue, as Treré argues that "t*he identification of an other and the delineation of boundaries are the main mechanisms of collective identity formation*" (2015:908). This view resonates well with framing perspectives on social movement, in which Benford and Snow argue that "*movement actors are viewed as signifying agents actively engaged in the production and maintenance of meaning for constituents, antagonists, and bystanders*" (2000:613). Thus, the joint engagement in the production of meaning and identity is important also for the production of solidarity within group boundaries. As Diani argues, boundaries imply "*a symbolic definition of an "in" and an "out," such as that feelings of belongingness and solidarity and identities are likely to be more present inside a certain group/collectivity than outside*" (2015:81). Therefore, to operationalize boundary definition in the MoC framework, I opt to use topic overlap between AAS-groups as a proxy of their closeness in terms of collective identity. The empirical analysis of topics has shown that they resemble frames much more than issues, as in the homogeneous set of AAS-groups, the debates were largely consensual. In other words, while a topic like "migration" might, for example in different parties' manifestos, be debated from various angles and perspectives, we have seen that among AAS-groups, this is not the case. The discussions analyzed here have rather served to establish a common framing of the various issues related to migration (sexual violence, crime, integration, etc.) and likely reassured the participants of these debates in their understanding of in- and out-group. The analysis has shown a clear identification of a collective "we" as the concerned, reasonable, and peaceful citizens of Germany, and the various out-groups of politicians, leftist mainstream society, lying press, or migrants. Therefore, in the following section I take the network of topical overlap in the debates of AAS-members as an additional indicator boundary definition in the MoC framework.

Network Construction

As the structural topic model used in the content analysis included each AAS-group as a covariate, one of the results of the model is an estimate of the effect that being from one group has on the expected proportion of a topic. Or, put simply, the model tells us whether some topics are more prevalent in one group than another. This can be interpreted as an affiliation matrix of dimensions 182x13, containing the effect for each of the 182 AAS-groups that produced enough data for the model, and each of the 13 topics identified by the model. The matrix was dichotomized, assigning a zero to effects below .1 or standard errors above .05, and a one otherwise, to qualify only relatively strong associations of a group with a topic. Using matrix manipulations analogous to the construction of the other networks, we can thus obtain a 182x182 adjacency matrix which informs us of the number of topics two groups are jointly affiliated with. The three groups not in the model were added as isolates to keep network measures comparable. The results of this raw network of topic overlap are shown in the left column of Table IV.23. As the density score shows, 52 per cent of all possible connections do exist in such a network. However, most of the 8,890 edges are fairly weak, as the mean and median edge weight illustrate. As weights lie on a scale from one to four (topics), and thus are more comparable than in cases of larger scales, I opted for a naïve cutoff for edges below the weight of three to reduce complexity and introduce a more clear-cut network. This network should reveal the structure of topic overlap more clearly.

Table IV.23 Properties of the topic overlap network before and after edge reduction

Network Properties	Before Reduction	After Reduction
Nodes	185	185
Isolates	3	93
Edges	8,890	342
Density	.522	.020
Range of edge weights	[1 – 4]	[3-4]
Mean edge weight	1.325	3.056
Median edge weight	1	3

Applying this edge reduction leads to a network of 92 AAS-groups connected by 342 groups, thus reducing the density to .02 for the entire network, or .08 calculated for only non-isolated nodes. The mean weight of 3.056 illustrates that an overlap of four topics between two groups remains the exception under these conditions and most edges will mean that the members of two groups were strongly engaged in debating the same three topics within their discussions. Analogous to our previous analysis, the following sections will discuss this networks on the levels of graph, nodes, and communities.

Graph

Identical to the four analyses of networks so far, we discuss graph-level properties in a comparative perspective, as illustrated by Table IV.24.

Table IV.24 Structural properties of the recognition, information sharing, co-mobilization, co-membership, and topic overlap networks

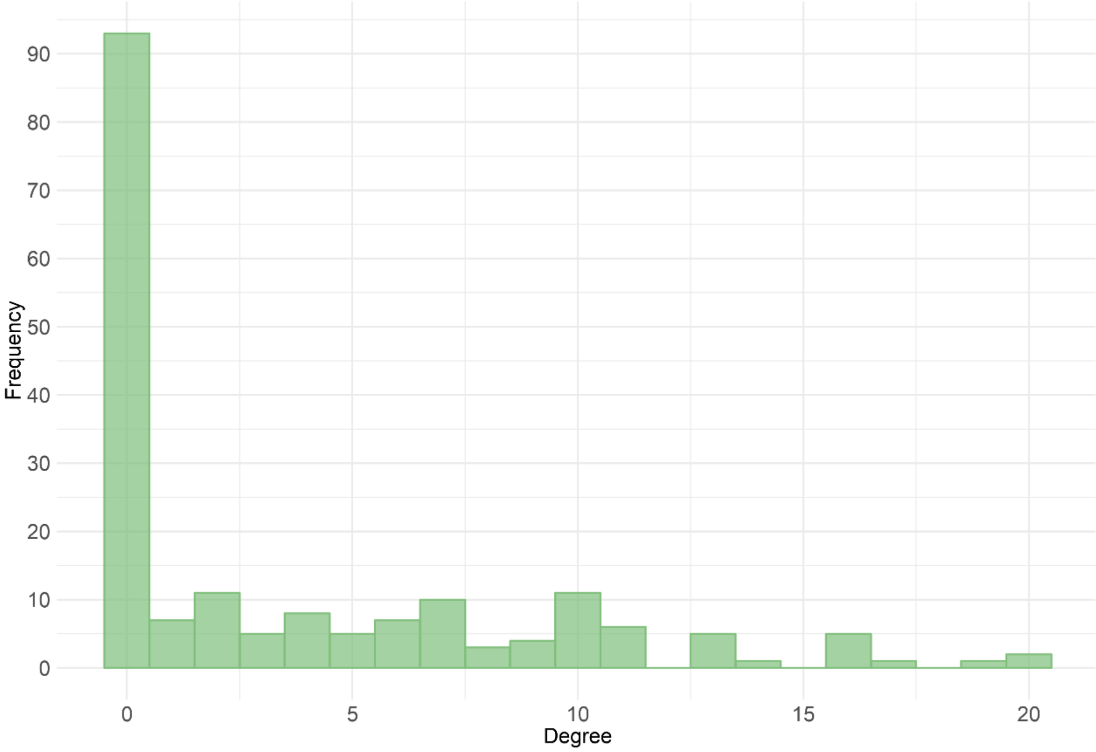
Measure	Recognition	Information Sharing	Co-mobilization	Co-membership	Topic Overlap
Directed	Yes	No	No	No	No
Weighted	No	Yes	Yes	Yes	Yes
Edges	579	941	38	589	342
Range of edge weights	n.a.	[3 – 3,827]	[3 – 17]	[3 – 678]	[3-4]
Mean edge weight	n.a.	39.9	5.29	43.77	3.06
Total edge weight	n.a.	37,542	201	25,781	1,045
Density	.017	.055	.005	.035	.020
Reciprocity	.18	n.a.	n.a.	n.a.	n.a.
Isolates	29	26	148	47	93
Fraction of Isolates	.16	.14	.80	.26	.50
Components (isolates excluded) weak/strong	1/3	1	6	3	2
Maximum Component Size weak/strong	156/53	159/n.a.	15/n.a.	131/n.a.	90/n.a.
Average Path Length	3.67	2.42	2.29	2.14	3.30
Connectedness weak/strong	.71/.08	.74/n.a.	.001/n.a.	.51/n.a.	.24/n.a.
Centralization (in-degree)	.12	.46	.04	.52	.09
Centralization (out-degree)	.29	.46	.04	.52	.09
Transitivity	.20	.32	.24	.25	.60

In comparison we can see that topic overlap is the more exclusive of the two boundary definition networks, leaving 50 per cent of the network isolated and only 90 groups connected in the largest component of the network. Smaller values are only found in the co-mobilization network which signifies deep collaborative ties. A comparatively long average path length, the lowest centralization scores of all networks and the highest transitivity values hint at a modular structure of the network. This means that unlike for example the co-membership that was centered around two exceptionally strong groups, we can expect to find several cohesive clusters that are interlinked, leading to long average paths and no clearly identified center of the network. This structure may result from different sets of groups simply debating the same set of topics.

Nodes

Again, we begin a node-level analysis with a look at degree-centrality as an indication of the connectedness of single groups. The distribution of degree in the topic overlap networks varies from that of other networks, as Figure IV.30 shows. While the highest bin contains all 92 isolates in this network, degrees ranging from one to 20 are more or less equally distributed, as the low centralization score already suggested. Thus, we do not see the familiar patterns of many groups being poorly connected to a few highly central groups, but instead many groups having a middle-range centrality in terms of degree. With the centralization and transitivity scores in mind this may be due to the tendency of groups being well connected in their section of the network, with only few groups that sit in brokering positions between these subgroups. As this position would be captured by a group’s betweenness centrality, we can more meaningfully distinguish central actors in the network through this measure.

Figure IV.30 Histogram of degree distribution in the topic overlap network



While the groups with the highest degree centrality are BB10, SN05, ST12, and ST01 with 20 ties for the first two, and 19, respectively 17 ties for the seconds two, the ones with the highest betweenness centrality are BB10 (989), SN38 (868), BB13 (834), and HE01 (794). None of these groups have featured prominently in any of the other networks discussed so far, meaning that centrality in this network does not correspond to centrality in others. Nonetheless, we recognize a pattern where groups from either Saxony or Brandenburg play central roles, with BB10 being a key group in both centrality measures. In general, a node-level inspection in this type of network serves rather to illustrate how certain graph-level properties play out on a micro-level. What is surely more important is the question which cohesive subgroups can be identified, i.e. communities which, through their common framing of migration-related issues as well as in- and outgroups, have a stronger potential for the development of a collective identity.

Communities

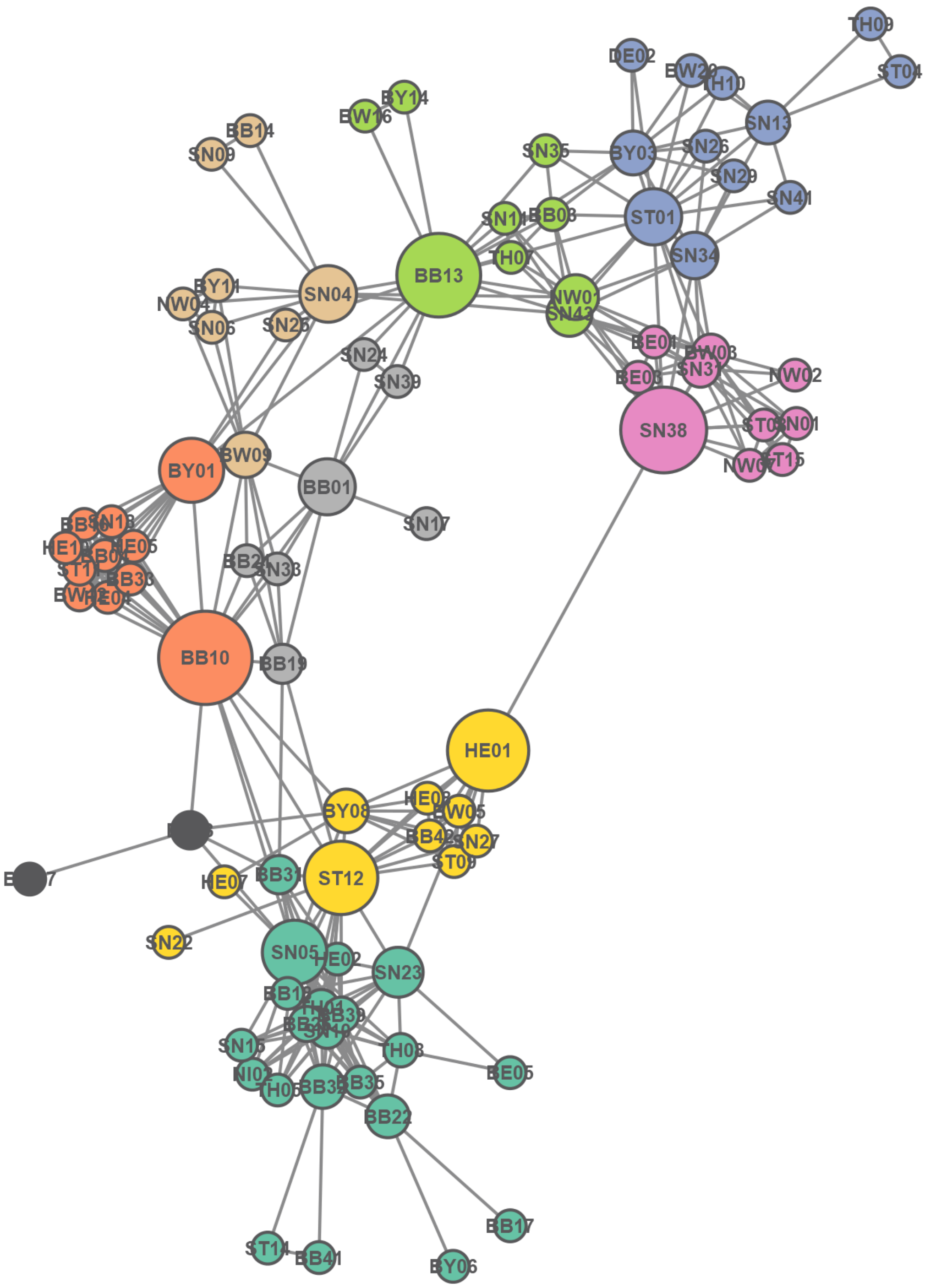
I used the biggest component (nodes=90) for a community detection with the Infomap algorithm to identify cohesive subgroups, meaning sets of AAS-groups that have higher overlaps of topics among themselves than with the rest of the network. As we might expect from the graph and node level analysis, there is a clear community structure with a modularity value of Q=.64 for a partition in nine communities, five of which have at least ten members. Unlike in our other networks, we can read that no regional clustering seems to at work, as the high average distances imply. The structural properties of these are summed up in Table IV.25.

Table IV.25 Structural properties of communities of size > 9 in the topic overlap network

	C1	C2	C3	C4	C5
Nodes (fraction of Component)	21 (.23)	11 (.12)	12 (.13)	10 (.11)	10 (.11)
Internal Edges (fraction of Component)	84 (.25)	55 (.16)	28 (.08)	31 (.09)	30 (.09)
Total weight of internal edges (fraction of Component)	262 (.25)	165 (.16)	87 (.08)	96 (.09)	90 (.09)
Mean weight of internal edges	3.12	3	3.11	3.10	3
External Edges (fraction of Component)	17 (.05)	13 (.04)	16 (.05)	17 (.05)	17 (.05)
Total weight of external edges (fraction of Component)	51 (.05)	40 (.04)	48 (.05)	51 (.05)	51 (.05)
Mean weight of external edges	3	3.08	3	3	3
Density	.40	1	.42	.69	.66
Average Path Length	1.80	1	1.67	1.31	1.36
Centralization (degree)	.35	0	.39	.31	.22
Centralization (betweenness)	.17	0	.32	.10	.20
Transitivity	.67	1	.59	.78	.92
Average edge length in km	221	370	183	398	315

Clearly, the communities form areas of higher internal density than the overall network, with scores of .40 to 1. While some networks have yielded partitions of unequally sized communities, the topic overlap network shows a remarkably equal distribution of community sizes, with only C1 standing out with 21 groups and the rest ranging between ten and twelve. As almost all edges in the network carry an equal weight, we must not give too much emphasis to the weights in this table, as they are included more for completeness' sake. C2 is a complete community with each of its members being connected to each other, leading to centralization scores of zero and density and transitivity of one. The other communities are also characterized by relatively high transitivity and density and middle-ranged values of centralization, meaning we find a structure of high cohesion among groups in a clearly fragmented network, where a few single groups occupy powerful positions at the intersections of communities. Figure IV.31 is a visualization of the largest component of the network. Node position is determined by the Fruchterman Reingold algorithm, while the colors represent the nine communities of the network. Node size corresponds to betweenness centrality. This clearly sums up what we have discussed above, as we see dense subgroups of topic overlap, which may signal a join involvement in identity construction, the definition and maintenance of symbolic boundaries, yet these subgroups are linked to the rest of the component by a number of central brokers. With this observation, we close the investigation of the different types of ties in networks of resource exchange and boundary definition, of the central actors within each, and of the structure of communities that did or did not evolve. These parts of the chapter sought to answer the research questions defined in RQ-set III, which were: *How do AAS-groups use social media? What types of ties amongst AAS-groups can be identified and what networks evolve from these ties? How do the types of ties correspond to mechanisms of resource allocation and boundary definition among AAS-groups?* In the analyses, we have learned that the rich data of interactions on the Facebook platform can be read as different types of ties, which, from a collective action perspective, correspond to different mechanisms of boundary definition and resource exchanges. From the different types and sizes of networks and in some cases different and in some cases similar groups who occupy central positions, we can read that SNS offer different affordances to organizations, and groups tend to make different usage of these. Thus, instead of treating social media or SNS as a black box that collective actors are either involved in or not, we have tried to untangle the various complex interactions and to study, who actually does what on Facebook and how different mechanisms lead to very different structural patterns, depending on the type and function of the network under investigation. Of course, these debates mark not the end but the beginning of a discussion on the applicability of concepts from (offline) collective action studies to digital data. Therefore, the analyses above must be read as a tentative proposal to apply the MoC framework and the two mechanisms within it to a case of digitally mediated collective action and test its exploratory power. To my knowledge, this is a novel approach and can surely benefit from a critical debate on its applicability and future comparative studies. Like in any research, we can easily imagine how the above classification of interactions into resource exchange and boundary definition in a digital setting might benefit from multiple cases and additional data to scrutinize the assumptions made and decisions taken. However, given the limitations of a dissertation, this will remain a debate to be held in further projects. For now, we will continue on the road taken and investigate the way different mechanisms combine to a typology of MoC and what might be the commonalities that determine the formation of networks of either mode.

Figure IV.31 The largest component (nodes=90) and its communities (colored) in the topic overlap network



Modes of Coordination

As said in the last chapter, we will continue to explore how different types of ties combine into the broader categories of Modes of Coordination of collective action. To do so, a first step will include initial steps of network and group comparison that are more formal, to find out how different types of ties relate to each other. This will both pave the way for and highlight the limitations of a combination of the adjacency matrices of each type of network into networks of the broader mechanisms of resource exchange, boundary definition, and finally MoC. Lastly, we will use exponential random graph models (ERGM) to identify and test determinants of tie formation in the combined networks, including the proximity to formal organizations of the political right. Thus, we can support the theoretical debate on the relevance of formal organizations in digitally mediated collective action with empirical evidence from this case. The analyses in this chapter thus correspond to the research questions asked in RQ-set IV, which were: *How do the types of ties identified combine into different Modes of Coordination of collective action? What properties of groups can explain their relational patterns, i.e. their mode of coordination? More specifically, does the proximity to formal organizations of the political right explain tie formation in different Modes of Coordination?*

Comparing Networks

While the previous chapters have already drawn comparisons between the different types of tie in a qualitative discussion of each, we can join these threads in a more systematic and single measure at this point. Thus, in a first step, we can assess the correlations between networks, or, more precisely, their dichotomized adjacency matrices. Table IV.26 shows the product moment correlations between matrices, calculated with the *gcor* function of the *sna* package (Butts 2016) in R. The Quadratic Assignment Procedure (QAP) was used to obtain significance scores. QAP is useful in both correlations and regression of matrices in general and networks in particular, which violate standard assumptions of independence. In QAP, a permutation, i.e. random shuffling of node labels in a network matrix, is used and the coefficient of interest (in this case correlation) is recalculated. Doing so 5,000 times produces a distribution of correlation coefficients obtained from random networks with identical structure. Counting the fraction of permutations that are higher or equal than the original observed coefficient produces the p-value in this case (for explanations of QAP see: Borgatti et al. 2013; Robbins 2015:190). Table IV.26 shows only the lower triangle of a correlation matrix, as it is symmetric with a value of one in the diagonal.

Table IV.26 Network correlation matrix

	Recognition	Information Sharing	Co-mobilization	Co-membership	Topic overlap
Recognition	-		-	-	-
Information Sharing	.28 ***	-	-	-	-
Co-mobilization	.25***	.35***	-	-	-
Co-membership	.09***	.21***	.16***	-	-
Topic overlap	.001n.s.	.01n.s.	.04***	-.007n.s.	-

*Significance levels: p ≤ .05 *, p ≤ .01 **, p ≤ .001 ****

Network correlations inform the researcher about the relationship between two matrices, asking if ties between the same actors exist in both networks, which is a common question in multiplex networks, i.e. networks of different types of ties between the same set of nodes[76]. In our case, we can see that being connected in the recognition network is significantly and positively associated with being connected by information sharing, co-mobilization, and, to a lesser degree, co-membership.

Information sharing is significantly and positively associated with co-mobilization, having the highest correlation of all networks, with a score of .35. This means that many actors engaged in one type of resource exchange are also engaged in other types. Weaker, but significant correlations exist to the boundary definition network of co-membership, which is most associated with information sharing, less with co-mobilization and weakly but positively with exchanges of recognition.

We can see that topic overlap stands out, with a significant but weak correlation only with co-mobilization, but not with the other dimension of boundary definition, which is co-membership. This could be due to the measurement and the way the network is constructed or it may simply mean that joint engagement in the same topics is independent of whether the same people are involved in that discussion (co-membership) and of whether groups are connected by resource exchanges. It might also be speculated that the relational pattern evolving from topic overlaps is simply not distinct enough to show significant correlation with other types of ties. In other words, the fact that we have highly homogeneous groups might produce networks that do not represent distinct mechanisms of boundary definition. The fact that our content analysis in chapter IV.ii has produced topics that often resemble different but very compatible frames of a single issue would further support this assumption. In the case of co-membership, the correlation misses the significance level of .05 only slightly,

[76] Classical examples in social network analysis would include the question whether friends also give advice to each other, or whether families engaged in business exchanges are also engaged in marriages (Padgett 1994).

but the coefficient is even slightly negative. Thus, on the one hand, we may substantially view co-membership and topic overlap as two distinct dimensions of boundary definition, but on the other hand, we must empirically be careful in the construction of an additive measure of boundary definition, as joining the two measures that have little in common can be problematic. This issue will be debated once we approach the task of combining networks in the next subchapter.

For now, we can add another comparative perspective that sums up the qualitative investigation of central nodes in each network in a more reduced measure of the rank correlation of groups' degree in each network. The correlation matrix reporting Kendall's tau is given in Table IV.27. Note that the directed network of recognition is divided by indegree and outdegree.

Table IV.27 Correlation matrix of degree centrality

	Recognition indegree	Recognition outdegree	Information Sharing	Co-mobilization	Co-membership	Topic overlap
Recognition indegree	-	-	-	-	-	-
Recognition outdegree	$.29^{***}$	-	-	-	-	-
Information Sharing	$.29^{***}$	$.24^{***}$	-	-	-	-
Co-mobilization	$.24^{***}$	$.15^{*}$	$.34^{***}$	-	-	-
Co-membership	$.39^{***}$	$.27^{***}$	$.46^{***}$	$.43^{***}$	-	-
Topic overlap	$.06^{n.s.}$	$-.05^{n.s.}$	$.09^{n.s.}$	$.10^{n.s.}$	$.05^{n.s.}$	-

*Significance levels: $p \leq .05$ *, $p \leq .01$ **, $p \leq .001$ ****

As we have seen, the centrality ranks between indegree and outdegree do correlate significantly, but not particularly strong. Especially for higher ranked groups, we could see that very popular groups (indegree) are hardly engaged in outreach (outdegree) and vice versa (see Figure IV.14). For lower ranked groups however, there seems to be a correspondence between outreach and popularity, which is expressed by a coefficient of .29. While being tied to each other in the recognition and co-membership network was not strongly correlated, being popular and having many connections of co-membership is, with a coefficient of .39. As co-membership is undirected, we do not know for sure, but can reasonably assume that members of other groups are drawn to popular groups where they also become involved, leading to co-membership ties. Ranks of degree centrality in the co-membership network are also significantly correlated with centrality in outreach (.27), information sharing (.46), and co-mobilization (.43). In other words, AAS-groups who are well connected by ties of co-membership also tend to be well connected through ties of information and co-mobilization. This confirms the impression of the investigation of key groups in each network, meaning that oftentimes, we find the same set of groups to occupy central positions in the different types of networks. Small, negative, or insignificant correlations might point towards a general functional differentiation, meaning different groups are central for different functions. This, however, is not the case, strengthening the impression that within the population of German AAS-groups, a hierarchy (at least in terms of degree centrality) seems to persist across different networks of boundary definition and resource exchange. The degree centrality ranks in most other networks correlate significantly with both popularity and outreach, but are stronger for more popular groups, meaning in general, central groups in other networks are more likely to very popular than very engaged in outreach. For co-mobilization, the strongest correlation both between networks (Table IV.26) and in terms of central actors (Table IV.27) exists to information sharing, supporting the impression that groups who are connected well by ties of information sharing are also the ones who are connected well by ties of engagement in protest activities. For topic overlap however, the impression of a network whose adjacency structure is largely detached from that of the others is supported by a lack of strong or even significant correlations in terms of central groups. Thus, the groups who occupy central positions in topic overlap are different ones than the central groups of other networks. This, however, limits the possibilities of creating a meaningful additive measure of social bonds, which will be the subject of the following section.

Combining Networks

So far, we have discussed the different types of ties among AAS-groups as separate networks corresponding do different functions within the mechanisms of resource exchange and boundary definition. To meaningfully distinguish between strong or weak engagement in either mechanism, I decided for an additive approach. This means summing up dichotomized adjacency matrices to a single network of resource exchange and boundary definition each, which in turn can be used to distinguish networks of stronger or weaker engagement in either dimension. This will enable us to look at each *network as corresponding to each MoC*. Thus, we do not characterize structural positions and their incumbents as MoC, but types of ties. In turn, we will also not focus on the shared properties of groups in each position, but instead on how group properties affect the probability of ties. As we have mentioned at the beginning of this chapter, this is probably the most significant departure from Diani's original operationalization of the framework. This is in no way a criticism, but rather a different focus on ties rather than nodes, equally consistent with a relational perspective and with the tie-based network models that are applied here. To understand this a bit better, we may briefly outline the way Diani (2015) and Eggert (2014) operationalized the MoC framework.

Structural equivalence lies at the heart of the attempt to divide networks into subgroups by comparing the distributions of ties of each member. We may call this a positional approach, as belonging to the same subgroup thus means having relatively equivalent ties, i.e. being in a similar position or role.[77] This does however not mean, that actors in a similar position are necessarily directly tied to each other, but are similar in their pattern of ties to others. To apply this approach, both Diani and Eggert use the CONCOR algorithm, which stands for CONvergence of iterated CORrelations, which, as the name suggests, iterates through correlation matrices of a network to eventually permute the resulting matrix into blocks that can be interpreted as relatively equivalent positions (Breiger et al. 1975). One of the problems associated with this procedure, however, is that the number of partitions does not necessarily reflect a "best fit" to the data but is determined by the researcher (Diani 2015:76). Once these blocks have produced a reduced image matrix of the original adjacency matrix, researchers can compare the distribution of within and across-ties between the different blocks identified, to see if blocks are not only equivalent but also cohesive. Techniques like homophily tests can thus be applied to test whether incumbents of one block are significantly more likely to be connected to other incumbents of the same block, or not. In Diani's operationalization, these blocks are derived from an adjacency matrix of resource exchanges. Social bonds, in turn, are empirically defined as a subcategory of these exchanges, namely those ties that *not only* involve resource exchanges*, but*

77 This understanding of a subgroup clearly differs from the cohesion-based definition of subgroups as communities of higher internal than external density, that was used throughout this thesis.

also by interpersonal ties of friendship of co-membership ties.[78] As such, these social bonds serve as a "reasonable proxy" for boundary definition (Diani 2015:84).

The combination of equivalent blocks and the distribution of these two types of ties can ultimately lead to a characterization of groups in terms of the MoC framework, as Eggert describes:

> *Organizations that display a social movement mode of coordination will hold the same position and send resource exchange as well as boundary definition ties within structurally equivalent blocks. In this case, we will find a positive relation between block membership and the relation — that is, resource exchange and boundary definition would overlap. In an organizational mode of coordination, neither the resource exchange network nor the boundary definition network will be related positively to membership in a block. If organizations display a community mode of coordination, only the boundary definition network will be positively related to block membership. And finally, a coalitional mode of coordination will give a positive relation for resource exchange but not for boundary definition* (2014:381).

I include this elaboration to illustrate where the following chapters will *depart* from it. When we look at Eggert's operationalization, for example, both resource exchange and boundary definition are each measured by several items in a survey. However, the matrices for both dimensions are *dichotomized* based on the criterion whether *at least one type of tie* is present. This discards the information whether or not groups may be involved in multiple ties of resource exchange or in multiple ties of boundary

78 This is different from Eggert's operationalization of the framework, which does not use social bonds, but either *resource exchange* ties or *boundary definition* ties.

definition. In contrast, my own approach so far has been very much focused on exploring the different types of interactions that result from groups' choices to make use of the various affordances of SNS or not. When exploring the role of SNS for collective actors, it is crucial to neatly separate each type of tie and explore them separately, to understand how they are used differently and what patterns emerge in each one. This accounts for the fact that organizations of the field can be tied in complex patterns of multiple relations. From this vantage point, we can quantify the *strength* of both resource exchange and boundary definition, by either qualifying the simultaneous presence of *multiple types of ties* as a strong exchange (resource exchange) or using the *valued* nature of our data on co-membership to distinguish between strong and weak ties (boundary definition). While the exact definition of strong and weak ties on either dimension will be subject to the following sections, it suffices to say at this point that this distinction between strong and weak ties in either dimension serves my operationalization of the four quadrants in the typology of MoC. The advantage of this approach is that is does not place groups in distinct categories but allows each group to be involved in ties of multiple modes, albeit with different alters and with different intensity. Thus, we can not only find "*multiple logics of action within empirical episodes of collective action*" (Diani 2015:4), but we can also find organizations involved in multiple logics. Ultimately, this does not contrast but rather complement a positional approach. Ideally, we would apply both operationalizations in a single project to compare weaknesses, strengths, and result. However, I believe this comparison is beyond the resources of this project. Thus, I will now continue with the tie-based operationalization of the MoC framework and illustrate its results.

To do so, the following section will briefly illustrate the steps taken to combine the different networks to two dimensions and discuss the operationalization of weak and strong tie in each dimension. This is illustrated by a description of the various networks that emerge from these choices. After that, the next section will discuss the group-level properties that determine the ties for each type of MoC-network, to study what might foster or hinder groups' coordination on one mode or another.

Resource Exchange

The aggregated network of resource exchange among AAS-groups includes the recognition network, the information sharing network, and the co-mobilization network. The former is *dichotomous* and *directed*, as there is either a positive nomination of group B by group A, or there is not, while the latter two networks are *undirected* but *weighted*, as the joint engagement in the distribution of content and news stories and the joint mobilization for contentious events can be stronger or weaker. Naturally, any reduction of the complexity of data comes at the cost of a loss of information and we must weigh between the two. In this case, I opted for an approach that symmetrizes and dichotomizes the adjacency matrix of recognition, counting any connection, even mutual ones, with a value of one. The matrices of information sharing and co-mobilization were also dichotomized, thus losing the information of the weight of any tie. This is surely a disadvantage of the approach, but we must bear in mind that the backbone approach has already filtered out insignificant weights, which means we at least avoided the fallacy of pooling insignificant weak edges with significant strong ones. Adding the three matrices yields a symmetric 185x185 matrix with values between zero, where groups are unconnected in either form of resource exchange, to three, meaning they are connected in all three forms.

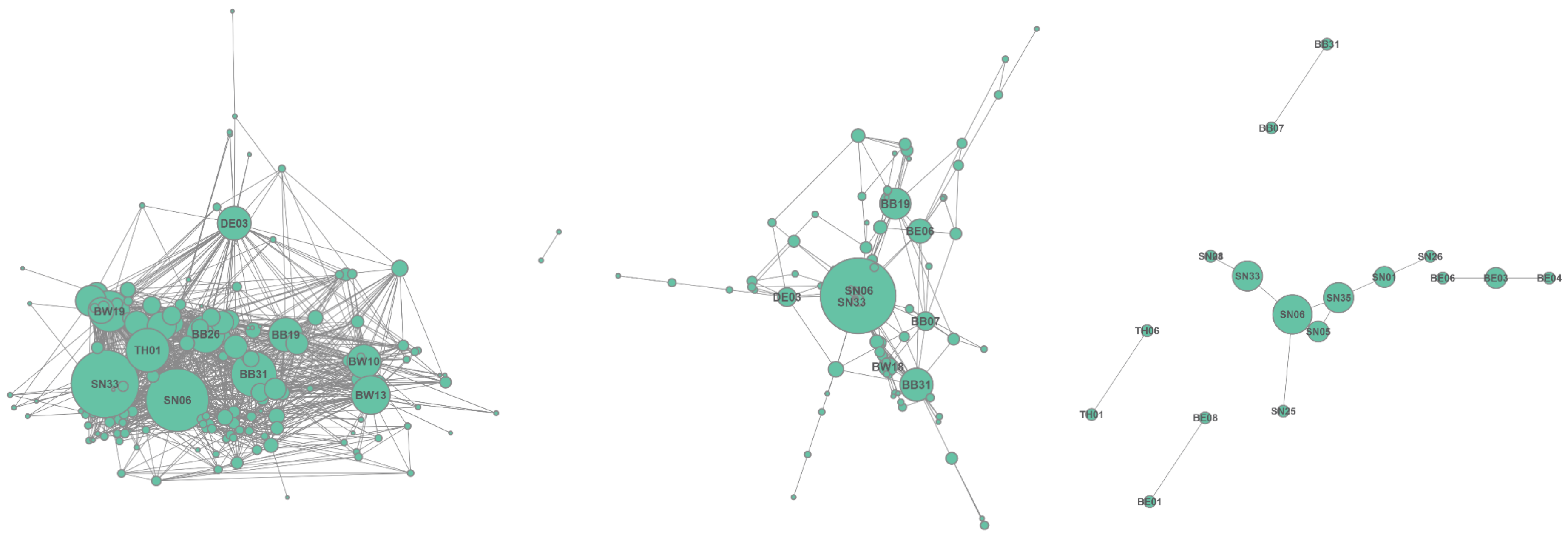
The question that arises next is *what value qualifies between weaker and stronger forms of resource exchange*. Table IV.28 sums up the properties of networks that arise when we construct networks with a) either form of resource exchange qualifies as a tie, b) at least two forms of resource exchange in common qualify as a tie, or c) all three forms of resource exchange must be present between a group to count as a tie.

Table IV.28 Structural properties of resource exchange networks with different cut-offs

Measure	Value ≥ one	Value ≥ two	Value = three
Edges	1,275	217	14
Density	.075	.013	.001
Isolates	9	70	167
Fraction of Isolates	.05	.38	.90
Components (isolates excluded)	1	2	5
Maximum Component Size	176	113	9
Average Path Length	2.25	3.29	2.24
Connectedness weak	.90	.37	.002
Centralization	.51	.21	.02
Transitivity	.30	.17	.20

From the table we can read that in total, 1,275 ties exist between AAS-groups that signal a connection in at least one form of resource exchange, corresponding to a density of .075. This leaves only five per cent of AAS-groups isolated, with the remaining 176 groups connected in one giant component, leading to a connectedness of .90. Degree centralization is .51, and the average distance between groups is 2.25, meaning we are likely to see a core of very well-connected groups and many groups directly connected to this core. The clustering coefficient is at .30, indicating a medium-low tendency of triadic closure. Reducing the edges of the network to those who signal two or three forms of resource exchange between the same two groups naturally reduces density of the network – in this case to .013 and .002, as only 217 and 14 edges are left, respectively. This also increases isolates, leaving 37 per cent unconnected in the middle column and 90 per cent of nodes isolates when applying the strictest criterion of connection. This is inversely related to connectedness, meaning the more isolates there are, the fewer reachable pairs exist. In addition, the network becomes more partitioned in each step, meaning that edge reduction leads to up to five components of mostly connected pairs instead of a single, small, but strongly connected network. This explains the low degree centralization of the latter network, as there can hardly be dominant groups when the network falls apart into tiny components. The network of at least two common forms of exchange has a comparatively long average distance between groups and a low clustering coefficient, meaning we are likely to see longer “chains” of connected nodes rather than a compact cluster of connections. Figure IV.32 offers a comparative overview of the three networks that result from different cut-offs for resource exchange. Separate MDS layouts define node position in each of the networks, while node size corresponds to degree centrality, calculated for each network separately. Labels are printed for nodes of degree above 50, eight, and zero, respectively. Next to an illustration of the structural properties discussed above, we can read the labels as indicators of which groups are central in all three forms of resource exchange.

Figure IV.32 Resource exchange networks



On the one hand, we can see that some groups who are well connected when counting any type of resource exchange, become unconnected when stricter criteria are applied: While the visualization to the left shows groups from Baden-Württemberg (BW-label) and the Germany-wide DE group as having more than 50 connections, they become isolated when looking at ties that count more than one form of resource exchange. On the other hand, we can clearly see that groups who have featured prominently in the discussion of separate networks are also the ones who remain central even when applying stricter criteria. This is especially apparent for Saxony- and Brandenburg-based groups (SN and BB labels). In addition, the strongest type of ties exists exclusively among geographically close groups, as the components shown in the right visualization are clearly demarcated along the lines of German Länder. This means that the strongest forms of resource exchange, even when digitally mediated, seem to strongly correspond to spatial proximity of groups.

For our purpose of combining resource exchange and boundary definition into a typology of MoC, we must decide what exactly qualifies as "*intense*" and what qualifies as "*limited*" (Diani 2015) in terms of either dimension. For the remainder of this study, I opted to treat any pair of groups connected by *at least two forms of resource exchange* as being in *intense* engagement, while any pair of groups connected by *only one* form of resource exchange as being in *limited* engagement. Note that the latter is not to be confused with the network discussed above, which has shown groups engaged in *at least* one form of exchange. Of course, this decision can be regarded arbitrary to some extent, but as we have seen, applying a criterion too strict severely limits the cases for a later comparison of the properties of actors in either mode. Additionally, as the analyses have shown, all three practices of positive nomination, of information sharing, and of mobilizing for contentious events, are far from excessive among AAS-groups. Thus, a joint involvement of two groups in two of the three networks can already be regarded as a strong form of instrumental tie between these groups. Nonetheless, the inspection of even stricter cut-off values was far from pointless, as we have gained the insight that a network of resource exchange among groups exists even when accounting for all three operationalizations and we have discussed how this network is shaped and composed. Thus, despite settling for a more relaxed definition of intense exchanges, we can nonetheless keep the central actors and underlying tendencies of tie formation in mind. That being said, we may now turn attention towards the second dimension in the MoC framework, which is boundary definition. The following section will discuss both the problems encountered, and the decisions taken in this regard.

Boundary Definition

As the comparison of matrices and actors has revealed, constructing an additive measure of boundary definition analogous to that of resource exchanges bears only limited potential. As this project nonetheless requires a measure that can distinguish between intense and limited engagement in boundary definition, I will propose an alternative based on the weighted measure of co-membership. As co-membership has been found to be a good indicator of boundary definitions in both Diani's (2015), and Eggert's (2014) application of the framework, I opt for this measure over the more experimental network of topic overlap. That being said we can compare the networks that emerge from an addition of the dichotomized adjacency matrices of co-membership and topic overlap versus a dichotomized version of the co-membership network that uses the *average weight* as a cut-off point. In the former approach, edges carry a weight of two when two groups are connected in both types of boundary definition networks (second column in Table IV.29) and a weight of one, when groups are connected in only one of the two networks (first column). Groups that are not connected in either network also remain isolated in the aggregated networks. In the latter approach, we can compare the original co-membership network (third column) with the one that only keeps edges of above average weight (fourth column). Table IV.29 provides an overview over the networks that result from either method.

Table IV.29 Structural properties of boundary definition networks using different approaches

Measure	Topic overlap and co-membership value ≥ one	Topic overlap and co-membership value = two	Co-membership	Co-membership above average
Edges	912	19	589	142
Density	.05	.001	.03	.008
Isolates	27	159	49	146
Fraction of Isolates	.15	.86	.26	.79
Components (isolates excluded)	1	7	3	2
Maximum Component Size	158	12	131	37
Average Path Length	2.34	2.31	2.14	1.99
Connectedness	.73	.006	.5	.14
Centralization	.50	.04	.51	.15
Transitivity	.30	0	.25	.50

We can read that 912 ties exist between AAS-groups when counting at least one form of boundary definition, corresponding to a density of .05, leaving 27 isolated groups and the rest connected in one component, leading to a connectedness of .73. Degree centralization is .50, and the average distance between groups is 2.34, again indicating a core of well-connected groups and many groups directly connected to this core. The medium-low clustering coefficient of .30 reduces to zero, meaning no triangles exist in a network that only counts ties between groups who are connected in both forms of boundary definition. This strict definition leaves only 19 edges between 26 groups, meaning that 86 per cent of groups are now unconnected. This sparsity of edges is the result of the two original networks being uncorrelated. In addition, the 26 groups are further partitioned into seven components, six of which are merely pairs of groups. Thus, many isolates and a fragmentation in components lead to a connectedness of only .006. In such a small network, a meaningful interpretation of centrality and path length is impossible, and we can thus move on to the alternative proposal of operationalizing intensity in boundary definition networks. This is shown in the already known properties of the co-membership network versus a dichotomization at the mean edge weight, shown in the fourth column of Table IV.29. We can see that this criterion is a strict one, reducing the number of non-isolated groups from 136 in the original co-membership network to 39 in a network of intense ties. These are further divided in one pair of groups and a component of 37 groups, being weakly centralized (.14), having short average paths (1.99), and thus being more clustered (.50) that the original network. Calculating density counting only non-isolated nodes (not shown in table) would result a fairly high value of .19 for the reduced network versus .06 for the original co-mobilization network. Thus, we can conclude that an additive approach leaves us with barely a network at all, while the reductive approach leaves a dense network of groups with strong ties of overlapping membership.

The former is a finding in substantive terms that must not be understated, as we can learn that obviously, the two dimensions of boundary definition as we have operationalized them, have little in common – nonetheless, a few groups do exist who are connected both by ties of co-membership and by ties of topic overlap. The second approach, however, enables us to distinguish between intense and weak engagement in boundary definition ties, albeit limited to a single indicator. The small but strong and dense network that emerges from this procedure enables us to combine intense and weak exchanges on both axes of the MoC framework and hopefully leaves enough cases in each type to as least tentatively compare the characteristics of groups engaged in either mode. Nonetheless, when we proceed to the combination of resource exchanges and boundary definition into MoC, we must be aware of the limitations imposed by the choices made in the operationalization of each concept.

Before we do so, Figure IV.33 allows for a visual inspection of the different networks that result from the operationalizations outlined above. From left to right, the figure shows a network of either type of boundary definition tie, a network with ties only for both types of boundary definition, and a network of only intense ties in co-membership. This corresponds to the columns of Table IV.29, with the exception of the non-reduced co-membership network (column three) that has been discussed separately before. In the left and right networks, MDS layouts determine node position, while the center one uses the Fruchterman Reingold algorithm[79]. In each of the networks, node size corresponds to degree centrality, calculated separately, meaning that node sizes can only be compared within but not across networks. Labels are printed for nodes of degree above 40, zero, and four respectively. From the labels we can thus read whether or not the central groups remain identical across networks. For the groups DE03 and BB31, this is certainly the case, as regardless of the network, both groups have the highest degree centrality.

The figure in the middle also shows how the network falls apart into one rather small main component and six pairs of nodes when using both types of boundary

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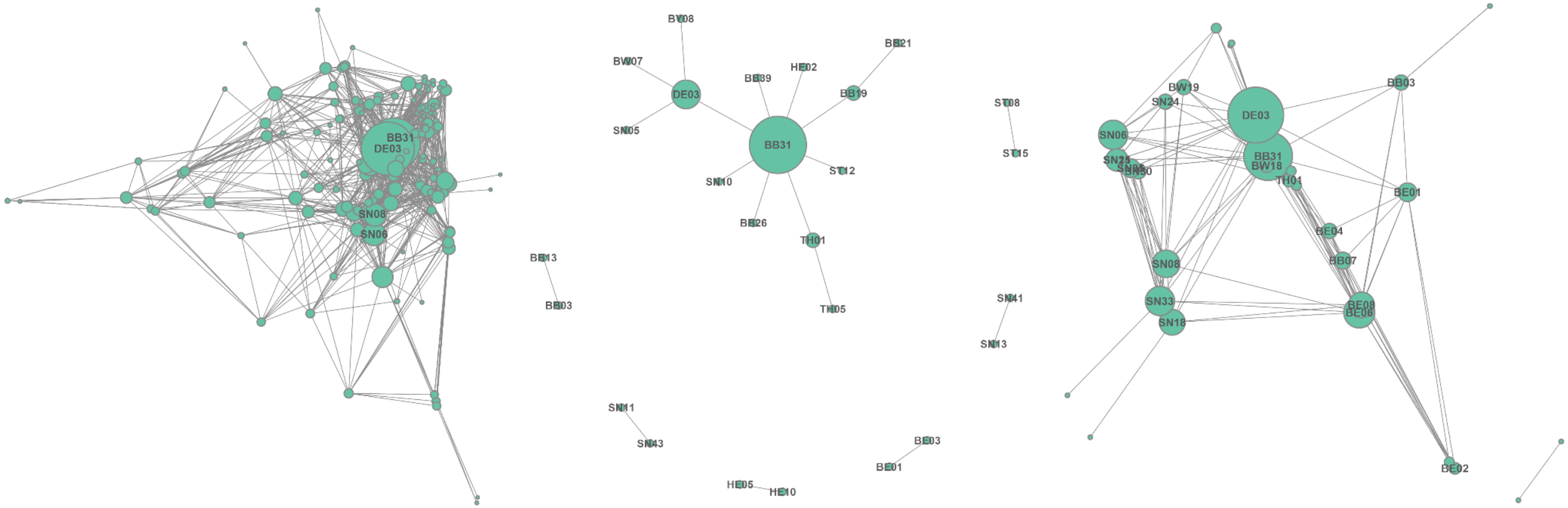
[79] This is due to the fact that several groups are connected to only one and the same other groups. A graphical representation of the two-dimensional scaling of the matrix produces identical positions in this case. Otherwise, the visualization is fairly similar.

definition combined. In all of the six pairs, the two groups come from the same German Land, meaning that the fragmentation has a clear geographical pattern in which spatially close groups remain connected amongst themselves but detached from the rest if the network. These spatial tendencies are not as prominent in the reduced co-membership network shown to the right of the figure. Nonetheless, we can read that groups from Saxony and the Berlin-Brandenburg area seem to be the main “survivors” of an edge reduction approach. The apparent difference lies in the centralization of the network, or more precisely the main components. In the additive approach, we clearly see an almost star-shaped network around BB31, and to a lesser degree around DE03, while in the reductionist approach, groups are not only connected to the most central groups, but also among each other, leading to a much higher number of triangles in the network. With that observation, we leave the intermediary step of describing resource exchange and boundary definition networks and come to the more salient part of combining these two. As discussed above, we will rely on the reductionist approach towards operationalizing boundary definition in the analyses to come.

These analyses will seek to answer the questions whether different Modes of Coordination can empirically be found in the data on AAS-groups, what properties the networks of interaction in different modes may have, i.e. how they are structured, and lastly what the determinants of tie formation in one mode or another are.

Figure IV.33 Boundary definition networks



Comparing modes

At this stage of the analysis, we will not engage in a deeper theoretical debate of the various MoC which have been discussed in-depth in chapter II of this dissertation. Instead, we will directly focus on the empirical manifestation of all four MoC, which are characterized by weak or intense interactions in terms of both boundary definition and resource exchange on the intergroup level. Again, we will empirically look at networks among AAS-groups that emerge from interactions at this level. This is distinct from an approach of qualifying groups themselves into discrete categories of MoC, as the latter would allow one and only one MoC per group. In a relational perspective, as I understand it here, MoC are not properties of AAS-groups but different *networks* that result from the various types of interaction. Thus, naturally one group can be engaged in different MoC at the same time, but with a different set of partners due to the different types of interactions. It is thus important to remember that in this perspective, MoC do not categorize groups but do categorize networks of interactions. Thus, this approach differs from a categorization of groups into positions according to the (structural or regular) equivalence. The latter often favors the discrete clustering of groups into blocks and then focuses analyses on the interactions within and across these blocks. Clearly, this is not the same as constructing different networks based on the intensity of connections, as in this approach, the members of these networks can overlap, but the ties cannot. This means we might identify the same actors, but in different constellations of connections, that are given by the nature of the interactions. In chapter II-vi, we have discussed this approach in more detail, which is focused rather on ties than on groups. Thus, it is more suited for analyses that focus rather on the structural properties of these networks than on their composition, as well as analyses based on Exponential Random Graph Models (ERGMS), that allow to study the determinants of tie formation within different networks.

That being said, we can operationalize the *organizational* mode by adding the dichotomous adjacency matrices of weak interactions in resource exchange and weak interactions in boundary definition and subsequently dichotomize the resulting matrix at a value of two, meaning that only ties between groups are kept that are present on both dimensions. This naturally excludes cases where there is either weak interaction in terms of resource exchange *or* boundary definition. The *coalitional* mode however is operationalized by adding the dichotomous adjacency matrices of strong interactions in resource exchange and weak interactions in boundary definition and subsequently dichotomizing the resulting valued matrix so that only ties exist when two groups are engaged in weak interactions on the boundary definition dimension *and* strong exchanges on the resource exchange dimension. Analogous to that procedure, we can use the matrices of resource exchange and boundary definition to qualify the *subcultural* mode, characterized by intense exchanges in the boundary definition dimension and weak interactions on the resource exchange dimension, and the *social movement* mode, qualified by intense exchanges in both dimensions. Based on networks of these ties, we can take a closer look at the prevalence of ties on either network, the size, and the structure of these networks. Ultimately, this thesis has asked for the role of SNS in the formation of collective among grassroots organizations of the political right. Thus, comparing the networks that correspond to different modes can help us answer this question, as we can learn, what combinations of interactions are more prevalent that others and what networks can emerge from the coordination of collective action in digitally mediated communication.

Table IV.30 sums up the features of each of the four networks in a comparative perspective. We can see that the above transformations have qualified 158 ties as organizational, 81 as coalitional, 51 as social movement, and 50 as subcultural, thus signaling a prevalence of organizational ties in the overall picture of AAS-interactions. This also means that varying numbers of groups remain isolated in the different networks, with the smallest being the subcultural one (154 isolates/31 non-isolates), followed by social movements (153/32), coalitional (104/81), and organizational (91/94). The organizational, coalitional, and social movement networks, however, are partitioned into components. This means we observe three pairs of groups in the organizational network, eight pairs and three components of size three, four, and six in the coalitional network, and two pairs in the social movement network, that are detached from the main components of size 88, 52, and 28, respectively. Apart from these detached pairs, we witness a tendency to form a single large group of connected nodes in each network. Calculating the density scores for each of the main components, yields scores of .04 for the organizational ties, .048 for the coalitional ties, .108 for subcultural ties, and .130 for social movement ties. In other words, the latter two who include strong engagement in boundary defining ties, tend to be more cohesive than the former two. This means that among groups who are engaged in these types of ties, relatively more connections exist than in other forms of exchanges. However, as density tends to decrease with network size (in a larger network, it requires more resources to be connected to everyone, leading to smaller densities), we must remain careful with this interpretation.

Table IV.30 Structural properties of networks based on MoC

Measure	Organizational	Coalitional	Subcultural	Social Movement
Edges	158	81	50	51
Density	.009	.005	.003	.003
Isolates	91	104	154	153
Fraction of Isolates	.49	.56	.83	.83
Components (isolates excluded)	4	12	1	3
Maximum Component Size	88	52	31	28
Component Density	.040	.048	.108	.130
Average Path Length	3.27	3.84	2.82	2.61
Connectedness	.23	.08	.03	.02
Centralization	.15	.07	.07	.07
Transitivity	.07	.09	.16	.31
Communities within the biggest Component (Infomap algorithm)	12	12	4	5
Modularity of Solution	.53	.60	.18	.38

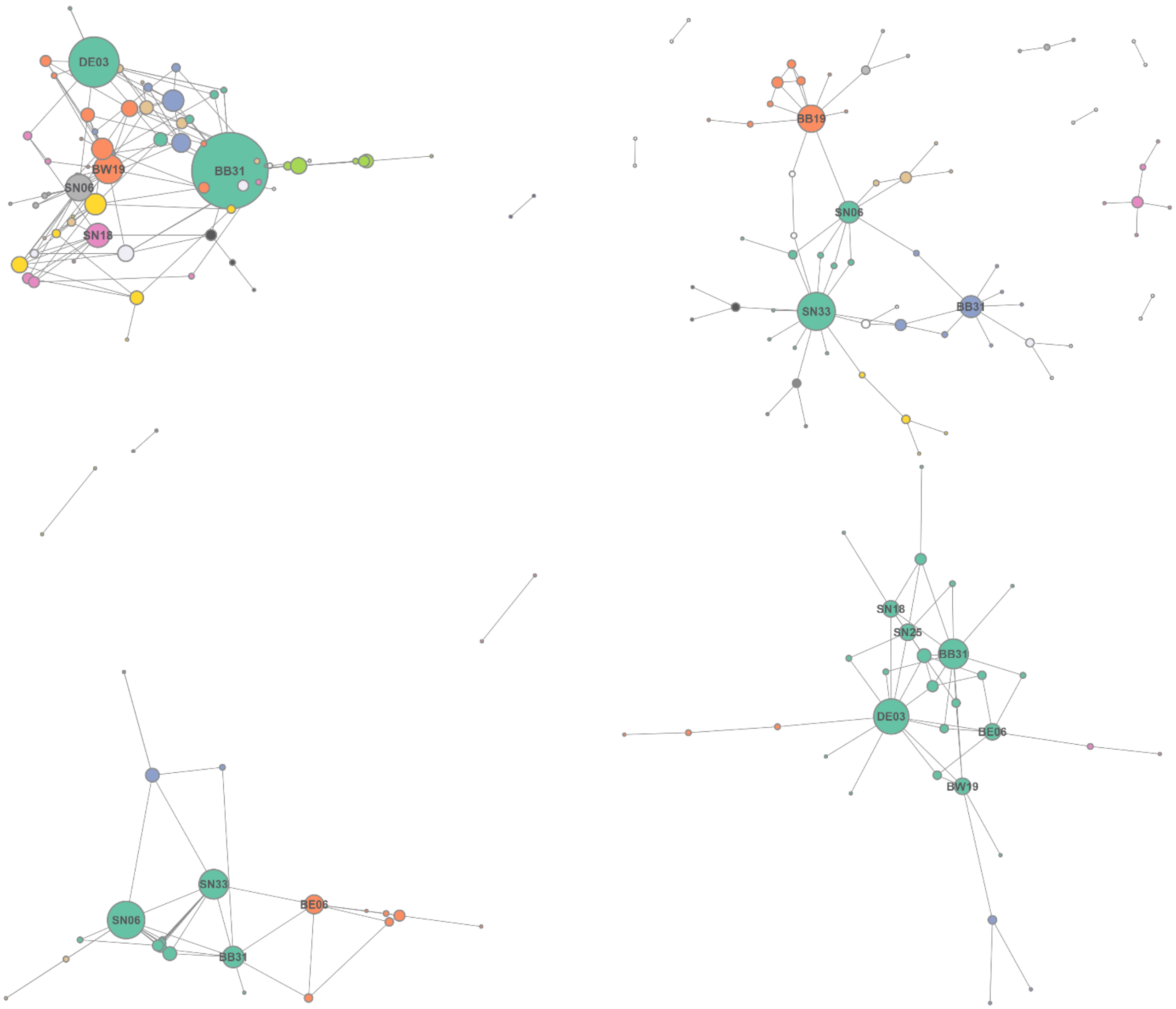
In addition, we observe a lower centralization (.07) in the subcultural and social movement network, meaning that degree is more evenly distributed across members of these networks. In other words, we are unlikely to find a concentration of ties on very few actors that dominate and control the network. In the sparser network of organizational ties, centralization tends to remain at .15, while coalitional exchanges also tend to be non-centralized (.07). This also corresponds to the average path length, which tends to be short in highly centralized networks, as many actors may reach each other through one very central intermediary. The longest paths are found in the coalitional and organizational network, which exhibit the lowest transitivity (.07/.09), and the highest modularity scores (.53,60) when the Infomap community detection algorithm is applied to its main component. In other words, organizational and coalitional exchanges in this case form networks of likely longer chains of smaller subgroups within overall sparse interactions. The modularity value is smallest for the subcultural network, which the algorithm also partitions into the smallest number of communities of all networks. This means this network shows the lowest tendency to form subgroups.

In summary, we can see that by far the most ties we observed among AAS-groups are of the *organizational* type, which are the least demanding in terms of intensity on either of the two dimensions of the framework. What might at first be surprising is the lowest density when we consider the main component of networks, along with the lowest transitivity and the second-highest modularity. However, we must consider that Diani's formulation of the organizational mode is characterized by organizations "*focusing on their own organizational boundaries and making limited investments in the building of broader collective actors*" (Diani 2015:167). From this perspective, despite the highest number of overall ties, the lowest density in the main component also means the lowest probability for the existence of an organizational type of tie. This is consistent with the findings by Baldassarri and Diani, who argued that strong ties of boundary definition "*embed associations into dense clusters of interaction, while more instrumental, ad hoc alliances ("transactions") operate across clusters, integrating them into broader civic networks*" (2007:771). In other words, the type of tie behind the organizational mode, as operationalized here, is unlikely to produce dense clusters of interaction among groups, but rather produces an instrumental, less dense (i.e. "looser"), network, when organizations follow a logic to "*invest in their own niche and do not exchange resources, or at least not at a significant level with other organizations*" (Eggert 2014:373). Nonetheless, the existing, yet casual, ties are able to integrate different groups into a broader collectivity.

In the organizational mode, we can also see a clear distinction between Diani's positional approach and my own tie-based approach. Clearly, the conceptualization of an ideal type of organizational mode allows the inclusion of organizations that work through their own agenda without the necessity to create neither ties of resource exchange nor ties of boundary definition, but instead campaigning and mobilizing entirely on their own. While Diani's operationalization of MoC would allow to subsume these groups in an organizational mode, my own focus on ties clearly comes at the cost of being unable to capture this behavior, as networks are created by default, if a tie exists. Nonetheless, as we have seen above, the low probability of such a tie is well in line with Diani's findings that this behavior is unlikely to produce dense networks.

But also, more intense forms of resource exchange, as shown in the *coalitional* network tend to produce a similar type of fragmented and relatively sparse network, although on a smaller scale. In fact, the partition into several components is even stronger, meaning that intense resource exchanges in the absence of intense interpersonal boundary defining ties lead to a fragmented network in which many groups tend to interact only with a few others. Apparently, this type of exchange leads to little triadic closure and cohesion. This is different for networks that include ties of intense *boundary defining* ties, like the *subcultural* network, which consists of 31 AAS-groups connected in a single component with relatively dense exchanges. However, we must remember that fewer groups in total are engaged in this type of network, meaning that even in the absence of strong resource exchanges, few groups are connected by strong interpersonal ties. A tendency toward a denser, more cohesive network with a higher degree of triadic closure is reflected in the *social movement* network. We identify exactly one tie and one group more than in the subcultural network, even though we apply a stronger definition of resource exchanges. This means this criterion does not have an adversarial effect on network size, but many groups engaged in in less intense forms of resource exchanges are also engaged in the stronger type, albeit with different partners. In this case, counting only intense resource exchanges, does not lead to the same degree of fragmentation as in the case between organizational and coalitional networks. Thus overall, a combination of intense exchanges on both dimensions leads to the densest network of all. In addition, a look at Figure IV.34 and Figure IV.35 illustrates the properties of these networks and shows that different groups are at the core or the coalitional and social movement and at the core of the organizational and subcultural networks.

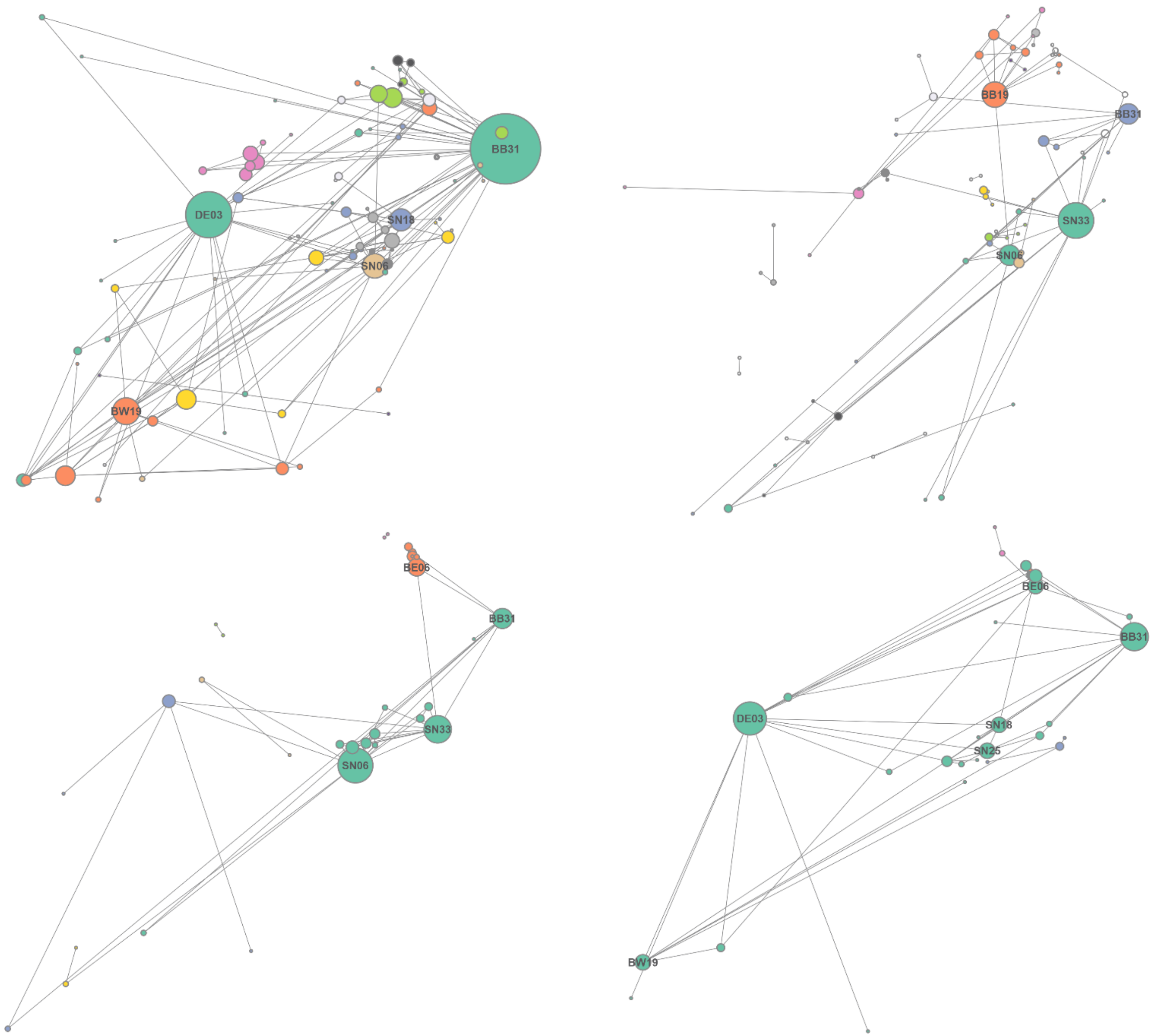
80 *Figure IV.34 MoC networks*



[80] Clockwise from top left: organizational, coalitional, subcultural, and social movement networks. Node position is based on MDS (organizational, social movement) and Fruchterman Reingold (subcultural, coalitional) algorithms. Node colors represent the results of community detection as described in Table 4.30. Node size corresponds to degree centrality. Most central nodes are labelled.

Figure IV.35 MoC networks in spatial layout

[81]



[81] Clockwise from top left: organizational, coalitional, subcultural, and social movement networks. Node position is based on geographic proximity. Node colors represent the results of community detection as described in Table 4.30. Node size corresponds to degree centrality. Most central nodes are labelled.

What is most revealing, however, is the tendency of stronger boundary definition ties, in combination with both weaker and stronger ties of resource exchange, to be spatially shorter, as we can read from Figure IV.35. Thus, it becomes clear that these ties based on the co-membership of users and thus focused on the possibility of interpersonal rather than intergroup exchanges, are less likely to bridge larger geographic distances than resource exchange ties.

Again, it must be noted that there are overlaps but also differences in the composition of each network, as only the ties are exclusive to either network, not the groups. This mapping of different types of ties to different MoC, thus clearly departs from Diani's original approach, which is less concerned with multiplexity, but rather with equivalence and positions. We thus reformulate the approach, focusing on the fact that the same actors may be involved in different relational patterns at the same time. In addition, the way we operationalized the different modes, mostly using an additive approach that has defined the presence or absence or multiplexity as a marker for strong and weak ties, departs from Diani's original approach based on the density of interactions. Each approach clearly comes with strengths and weaknesses, stemming from different foci and research interests. While Diani's formulation of MoC was centered on identifying different positions and their incumbents, our approach here is focused on identifying different ties and comparing the networks that emerge from each tie.

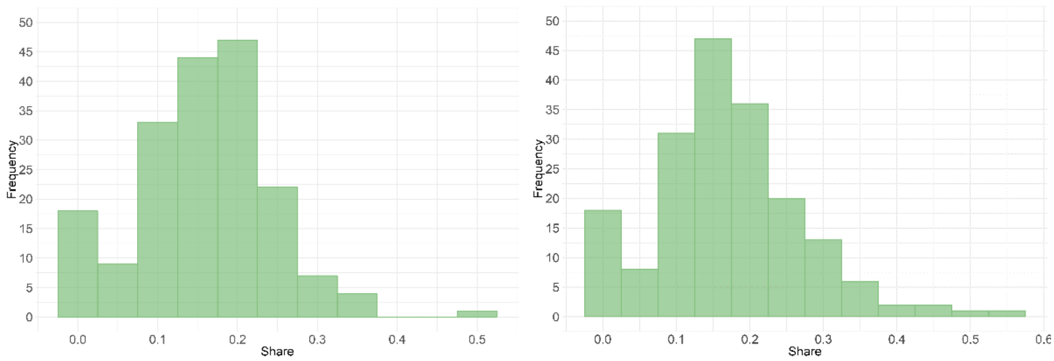
This has additional methodological implications, that will become more apparent in the following section, where we will assess the determinants of tie formation in each type of network. The visual inspections have, for example, clearly hinted at a relationship between spatial proximity and tie formation, that will be more systematically assessed in the following section. In addition, we will deal with the theoretically relevant question of the role of formal organizations in AAS-networks. After we have discussed the determinants of ties in either network, we will move on to a more thorough debate on the meanings and implications of the results of all empirical analyses. This will connect our empirical findings to the debates in chapter II.

Testing Determinants

In the last empirical analysis of this thesis, we will look deeper into the mechanisms behind tie formation in either of the four MoC, allowing us to answer the last of the research questions that asked for the properties of groups that may ease or hinder the interactions that corresponds to each MoC. We will thus run separate ERGMs with our networks to test which properties of groups' have a significant effect on the dependent variable, which is being connected in a network. Some of these properties have emerged from the results of previous analyses, like spatial proximity, which strongly seems to correspond to tie formation, especially in networks of stronger boundary defining ties. Thus, including *spatial proximity* has both a control function as well as offering the chance to more systematically assess the significance and relative strength of its effect across networks. We operationalize it in this case a categorical variable of the area code of each group, i.e. the German Land a group is from. Similarly, we have found an exogenous measure of popularity, namely the number of individual fans for every page, to correspond to endogenous popularity, namely indegree in the recognition network. Thus, a variable of the number of external fans can control for and asses *popularity* effects in our networks. The same goes for a group's overall activity, which has shown to vary greatly among AAS-groups. To account for the fact that groups may be connected just because they are very active, we will include total *activity* as a variable in the model. Lastly, another variable has its origin rather in the theoretical debate sketched in chapter II than in the exploration of results in chapter IV: The significance of formal organizations in the coordination of collective action has, as we have seen, been subject to debate in the study of digitally mediated collective action. Bluntly put, whether the technological infrastructure provided by ICTs in general and SNS in particular can render the importance of formal organization insignificant has been at the core of debates on digitalization and collective action. While we will not find definitive answers to this question from a single case and from the analyses of this thesis, we can nonetheless find out whether or not, in this particular case, formal organizations did play a role for tie formation among AAS-groups. From chapter III we have learned that two organizations, who are highly formalized and institutionalized, play a major role for Germany's (radical) Right. The older and more established extreme right-wing party NPD, and the newly emerged populist (extremist) right-wing party AfD. Of course, choosing parties to operationalize the role of formal organizations is not a comprehensive perspective on formal organization, but can rather serve as a reasonable proxy for the influence that these types of non-grassroots actors may exert. We will do so by looking at the interpersonal ties between AAS-groups and each of the two German right-wing parties, much like we operationalized boundary definition. To do so, we can use the more than 11 million observations on NPD and AfD activity, as described in chapter III-iii. Thus, for each AAS-group we can compute the share of users that also were active on the NPD's or the AfD's

Facebook page during the observed period[82]. Unfortunately, this data is undirected, thus unable to distinguish mechanisms of (hidden) influence of formal organizations on AAS-groups from the tendency of AAS-groups' members being drawn towards political parties. Figure IV.36 provides us with a view of the distribution of these values over all 185 groups. We can see that for each party, we find roughly 15 to 20 unaffiliated groups with an overlap score of zero. The non-zeros follow only slightly skewed distributions, with affiliation scores of up to about 50 per cent in both cases. For the NPD the mean overlap is .17, while for the AfD, it is .16.

Figure IV.36 Histogram of user overlap with the AfD (left) and the NPD (right) N=185



Thus, on average 16 per cent of the users active in an AAS-group during the observed period were also active on the AfD's main page while on average 17 per cent of users active in an AAS-group were also active on the NPD's main page.[83] This is already a substantial finding in its own right, meaning that even in the absence of comparative cases on right-wing grassroots mobilization, we may interpret these

[82] This method is similar to that applied by (Stier et al. 2017), who measured user overlaps between the right-wing PEGIDA group and seven German parties on Facebook. The results suggested a common supporter base between PEGIDA and the AfD (.33 for likes, .2 for comments) and smaller overlaps between PEGIDA and the CSU, with overlap values below .06 between PEGIDA and all other parties. This may suggest that also in the case of AAS groups, we are likely to find far less proximity to parties in the more democratic political spectrum.

[83] Adding data on the regional and local chapters of the respective party would probably reveal even stronger associations. However, due to the already huge amount of data for a single measure, I found this approach unfeasible.

numbers as a non-negligible affinity to formal organizations of the political right. In addition, these two sets of observation are significantly correlated (Pearson' r=.47, Kendall's tau=.33), meaning that we observe a tendency of groups being affiliated with both parties on a similar level. Nonetheless, as the distribution shows, this affiliation varies strongly across groups, allowing us to meaningfully assess whether a stronger affiliation to any of the two formal organizations may explain the formation of ties in our networks.

To do so, we will use ERGM's (Pattison, Kalish, and Lusher 2007; Snijders et al. 2006) as one family of statistical models for network data. The basic assumption of ERGMs is that ties in networks are treated as random variables and the models do "*not assume independence between the dyads but they also allow the specification and estimation of specific sources of dependence.*" (Lomi et al. 2014:447). In other words, ERGMs allow to test the effects of node attributes under the conditions of the "*endogenous parameters*" (Heaney 2014), like the prevalence of edges, reciprocity, closure, etc.. Thus, the properties of a network can be very explicitly modelled, thus allowing to "*examine the specific effects of individual attributes on network ties in a way that controls for endogenous network processes*" (Lomi et al. 2014). In our case, however, we will make limited use of the exact specification of endogenous parameters, as our interest lies not in exact modelling but rather testing the significance and direction of the effects of groups' attributes, as we have discussed earlier. Table IV.31 offers a baseline model calculated with the "ergm" package (Hunter et al. 2008) in R, specifying only edges as an endogenous parameter.

The coefficients in that model are the conditional log-odds for an edge to exist in each network. For the organizational network for example, we can calculate the probability of observing a tie with exp(-4.670)/(1 + exp(-4.670)), which results in .009, i.e. the *density* of this network. The negative coefficients tell us that we find networks sparser than expected by chance, with the lowest value for the subcultural network, which is the sparsest.

In a next step, we can add the affiliation scores to the model, separately for each party to test, whether affiliation with each of our two formal right-wing organizations has a significant effect in being connected in each MoC. From the models in Table IV.32 we can read that being affiliated with the AfD has a positive significant main effect on being connected in any of the networks of interest, albeit weakest in the coalitional mode and strongest in the subcultural mode. Affiliation with the NPD also has a significant positive effect on tie formation in each of the networks. In contrast to the AfD, we find this effect strongest in the coalitional mode, which is characterized by strong ties of resource exchange and weak ties of boundary definition. The least significant and weakest effect is found in the social movement mode, meaning that affiliation with the NPD is less associated with the simultaneous activation of strong boundary definition *and* resource exchange ties.

Table IV.31 Baseline models for MoC networks

Parameter	Organizational	Coalitional	Subcultural	Social Movement
	Model (1)	Model (1)	Model (1)	Model (1)
	Coefficient (standard error)			
Edge	-4.670^{***} (.080)	-5.343^{***} (.0111)	-5.827^{***} (.0142)	-5.807^{***} (.140)
N (dyads)	34,040	34,040	34,040	34,040
Akaike Information Criterion (AIC)	1,795	1,030	685	697
Bayesian Information Criterion (BIC)	1,803	1,038	693	704

*Significance levels: $p \leq .05$ *, $p \leq .01$ **, $p \leq .001$ ****

Table IV.32 Formal organization affiliation models for MoC networks

Parameter	Organizational		Coalitional		Subcultural		Social Movement	
	Model (2)	Model (3)	Model (2)	Model (3)	Model (2)	Model (3)	Model (2)	Model (3)
	Coefficient (standard error)							
AfD proximity	3.782^{***} (.656)		2.586^{***} (.925)		4.666^{***} (1.142)		4.368^{***} (1.136)	
NPD proximity		2.705^{***} (.519)		3.454^{***} (.702)		3.160^{***} (.900)		1.945^{*} (.931)
Edge	-5.970^{***} (.256)	-5.672^{***} (.222)	-6.210^{***} (.346)	-6.652^{***} (.314)	-7.462^{***} (.461)	-7.016^{***} (.397)	-7.328^{***} (.454)	-6.512^{***} (.384)
N (dyads)	34,040	34,040	34,040	34,040	34,040	34,040	34,040	34,040
AIC	1,765	1,772	1,024	1,010	671	675	684	694
BIC	1,780	1,787	1,040	1,025	686	691	700	710

*Significance levels: $p \leq .05$ *, $p \leq .01$ **, $p \leq .001$ ****

Let us stick with the example of the social movement for a while to explain how we may interpret the values in this model. As we analyze dyads, we can use the coefficient to inspect the probabilities of observing a tie in any combination of affiliation-score between two groups. As we said, we are basically looking at log-odds and can now calculate whether these odds, or rather the probability that can be derived from them, changes depending on the level of affiliation to the AfD or NPD. For a dyad of two groups that are unaffiliated with the NPD (affiliation score: 0), the probability of a tie remains at .001. In case both groups of a dyad are averagely affiliated with the NPD (affiliation score= .17 for both), the probability of a tie increases to .003. If both groups show a maximum affiliation with the NPD (affiliation score: .55 for both), the probability of a tie increases to .012. Of course, we may not only look at similarity in affiliation, but can also calculate the probability of a tie for a dyad, in which one of the groups is maximally affiliated with the NPD and one is not affiliated at all (affiliation score: .55 and 0). In this case, the probability is .004. Running these identical examples for the AfD, which has a much higher coefficient in the social movement network, yields values of .001, .003, .04, and .005.

Note that this is somewhat different from a homophily effect, that would tell us whether having a *similar level of affiliation* with formal organization increases the probability of being connected. Homophily is captured in Model (4) of Table IV.33, and from the negative coefficients we can read that a greater difference in terms of affiliation decreases the probability of observing a tie between two groups. In other words: we observe strong and significant homophily effects in all four networks. In addition, two tendencies can be observed: The strongest homophily effects for both parties can be found in the social movement network, and the homophily effect is generally stronger for the AfD than for the NPD. This means that groups with a similar level of affiliation to the AfD have a higher tendency to build ties among each other than with other groups. While this may be read as a strong source of creating tightly knit communities of similar actors, it might also hamper integration processes with different organization. The reasons for these processes may be manifold, however: On the one hand, homophily in this case may mean that groups affiliated with either of the two parties choose their connection according to the (perceived) similarity to other groups. On the other hand, it may also mean that groups with a high proximity to formal organizations are simply not successful in forging alliances with non-affiliated groups.

However, we must not overstate these results, as our analyses so far have clearly illustrated other patterns of tie formation that need to be controlled for. This is given in Model (5) of Table IV.33, which controls for popularity, activity, and spatial proximity. From the information criteria in all four networks, we can see that the inclusion of these controls, which are significant in all networks, improves the explanatory power of the model well over our baseline (smaller AIC and BIC).

Table IV.33 Formal organization homophily models (Model 4) and control variables (Model 5) for MoC networks

Parameter	Organizational		Coalitional		Subcultural		Social Movement	
	Model (4)	Model (5)	Model (4)	Model (5)	Model (4)	Model (5)	Model (4)	Model (5)
	Coefficient (standard error)							
AfD proximity		1.974* (.815)		.538 n.s. (1.143)		1.752 n.s. (1.638)		3.669* (1.432)
NPD proximity		2.667*** (.655)		4.529*** (.841)		2.760* (1.289)		1.388 n.s. (1.315)
AfD homophily	-11.104*** (1.785)		-13.328*** (2.680)		-10.395*** (3.073)		-24.162*** (4.628)	
NPD homophily	-5.168*** (1.310)		-4.896** (1.820)		-3.699 n.s. (2.158)		-7.149** (2.603)	
Popularity		-.0002*** (.00002)		-.0002*** (.00004)		-.0003*** (.00004)		-.0003*** (.00004)
Activity		.00003*** (.000003)		.00003*** (.000003)		.00004*** (.000004)		.00004*** (.000004)
Spatial proximity		2.096*** (.179)		2.769*** (.251)		1.978*** (.348)		3.121*** (.362)
Edge	-3.460*** (.142)	-7.342*** (.361)	-4.046*** (.197)	-8.514*** (.504)	-4.763*** (.251)	-9.099*** (.759)	-3.952*** (.245)	-9.715*** (.771)
N (dyads)	34,040	34,040	34,040	34,040	34,040	34,040	34,040	34,040
AIC	1,709	1,427	979	819	665	467	633	460
BIC	1,732	1,474	1003	866	689	514	656	507

*Significance levels: $p \leq .05$ *, $p \leq .01$ **, $p \leq .001$ ****

In general, we can see that being more active increases tie probability in all networks, while being more popular decreases probability. The small coefficients are due to the units of measurement – each user like and each activity are a unit increase in these variables. Thus, the numbers tell us that there is a positive activity effect and a negative popularity effect on tie formation in all four networks. The spatial proximity effect is significant and positive in all networks, but strongest in the social movement ties. This confirms our visual interpretation of Figure IV.35, where we found social movement ties to exist especially among spatially close groups. This means that strong boundary definition and strong resource exchange at the same time are partially explained by the geographic closeness of groups. This closeness may work in different ways and stand for different mechanisms at work: From our network of information sharing in chapter IV-iii, we have learned that local news sources are an important part of the overall information ecology of communities in the AAS network. Thus, the exposure to and interest in local or regional stories is an important property of our network. In addition, this goes hand-in-hand with strong co-membership ties, meaning that we can well consider the (often observed) possibility that these ties mirror offline acquaintance or collaboration. In other words: space matters and we find proximity to be a stronger predictor of tie formation in networks of stronger ties, either of resource exchange or of boundary definition.

However, our main interest in this empirical exercise was to better understand the role of formal organization for the formation of ties in either network of MoC. Adding the control variables to the model does change the outcome significantly. While Models (2) and (3) seemed to suggest generally stronger effects for affiliation with the AfD, this tendency does not hold when we control for other factors. Indeed, in two out of four networks, the effect of AfD proximity is not significant anymore, while it is barely significant in the organizational mode and the social movement mode. The effect of NPD proximity however is highly significant in the organizational and coalitional mode, barely significant in the subcultural mode, and not significant in the social movement mode.

Thus, being more affiliated with the NPD increases the likelihood for holding organizational ties and even more for coalitional ties, the same cannot be said for proximity to the AfD. We may speculate that a long-established party like the NPD might be better integrated in informal networks of the radical right than a relatively new addition to the party spectrum, and thus be able to utilize long-standing networks and former experiences of resource exchange. This is in line with observations on the political right that have shown the NPD's deep engagement in organizing demonstrations against migration, its involvement in the formation of vigilante groups in German small-towns and in the co-organization of festivals that serve as meeting points for right-wing (subcultural) groups (Kohler 2018; Mittelstädt 2018). Openly racist protest against migration in general and asylum-shelters in particular has long been on the agenda of the NPD, thus allowing groups with close interpersonal ties to this party access to a repertoire of tactics and information. That might explain why these groups are more likely to be connected in organizational and even more in coalitional ties. We may reasonably expect that being able to draw from a pool of resources and experiences provided by an established radical right party allows to play the role as a supplier of content and organizational resources within a network of AAS-groups.

However, when looking at exchanges that also involve stronger ties of boundary definition, i.e. the social movement mode of coordination, NPD-proximity does not have a significant effect on tie formation. Thus, the role of this party might be limited to that of a supplier of organizational resources, that is unable to (at the same time) permeate group boundaries and establish the interpersonal networks of solidarity. However, we do find a slightly significant yet not very strong effect of NPD affiliation in the subcultural mode, meaning that strong ties of boundary definition in absence of strong ties of resource exchange are also more likely. While this surely deserves a deeper investigation, we may, at this point, speculate that the party's involvement in the organization of cultural events like right-wing music festivals, might lead to interpersonal exchanges, without fostering organizational exchanges at the same time.

Thus, if the party’s engagement in subcultural events is aimed at mobilizing people to protest or campaign, our observation might be an indicator that this strategy fails.

In contrast, we find a slightly significant effect of AfD proximity on social movement ties. In other words, in a model that controls for the factors of proximity, activity, and popularity, a group closer to the AfD is still more likely to hold ties of strong resource exchange and strong boundary definition. This illustrates that unlike NPD proximity, AfD proximity seems to facilitate strong interpersonal ties in the presence of strong resource exchanges, meaning that groups closer to the AfD might be more successful in not only providing or disseminating information and event mobilization, but also in fostering interpersonal exchanges that might lead to deeper and longer lasting networks than coalitional and organizational exchanges. This is somewhat surprising, given that the AfD is a relatively new addition to the German party landscape, especially compared to the NPD. It might however be that it’s slightly less radical appeal and lower entanglement with radical right-wing groups may allow to bridge interpersonal differences, incompatibilities, or animosities. Given that, it is rather the simultaneous strong engagement in resource exchange ties that remains puzzling and should deserve further attention in future research.

Overall, these findings surely invite a deeper discussion of parties and movements, or movement-parties (Minkenberg 2018). We must, however, not forget that the point of our investigation was rather to use a proxy of formal organization affiliation to contribute to arguments on their role in digitally mediated collective action phenomena. This way, we tried to combine aspects of the logics of connective and collective with those of the MoC framework. From this perspective, we can conclude that formal organizations do - among other factors - play a role, even in a digitally mediated settings, which speaks for an intermediary logic between the ideal types of connective and collective action. This becomes clear through the lens of MoC, that was able to illustrate which types of networks emerge among AAS-groups, and to what extend these networks are influenced by the different roles of formal, hierarchical organizations. We could thus show that in our example, they do matter. But they matter differently, depending on the formal organization and depending on the mode of coordination under question. In other cases, the picture might look entirely different. This means that we cannot - and do not aim to – generalize the results from our exercise. Instead, we can illustrate the exploratory power of a framework that allows to make substantial and nuanced contributions to the role of formal organization in digitally mediated collective action.

While this chapter served primarily to present the results of empirical analyses, the following final chapter will discuss these finding in light of the theoretical debate sketched out at the beginning of this dissertation. It will also serve to highlight some of the shortcomings and limitations of the research design and point out pathways of future research that might address these gaps and further enrich our understanding of the relationship between collective action and SNS.

Chapter V - Summary, Conclusion, and Outlook

This dissertation started by asking about the role of social networking sites in digitally mediated collective action phenomena – not with the impossible aim of giving definitive answers or quantifying effects, but with the more modest target of adding to our collective understanding by drawing from different streams of literature in order to find a conceptual framework that allows for a clear and systematic analysis of digital data, genuinely rooted in relational perspectives to collective action.

As such, this piece is firmly grounded in an exploratory perspective. Exploratory in its attempt to understand rather than explain its subject: a novel form of protest groups against asylum-shelters in Germany, that is only beginning to draw scientific attention. Exploratory also in its operationalization of a relatively new conceptual framework, that has so far not been applied to digital data sources: The Modes of Coordination perspective on collective action. Therefore, I believe this dissertation has provided a pioneering attempt to our field, albeit the many challenges that are associated with innovation. Scientific diligence requires us to carefully address the limitations of this study, identify potential pathways to overcoming these, and thus sketch out the potential research agenda that can be drawn from these lessons. Before we do so later in this chapter, I want to start with the other important purpose of this section, which is a comprehensive and systematic assessment of the findings that were presented throughout the various analyses in chapter IV, especially in light of the research questions and theoretical perspective introduced in chapters II and III.

Before we recap these results, let us be reminded that our point of departure was marked by two observations. One the one hand, there is the ubiquity of social media in contemporary society in general and in collective action episodes in particular, leading to intense and controversial scholarly debate. This is what drives the theoretical interest of this thesis. On the other hand, there is an unprecedented rise of right-wing activity in post-war Germany, in political arenas, media discourse, and protest activity alike. This is what drives the substantial interest of this thesis.

The former observation was discussed in depth in chapter II of this dissertation. In it, I have argued to apply the framework of Modes of Coordination of collective action (Diani 2015), a perspective genuinely rooted in a relational view on collective action processes. While we have addressed the challenges of an application of this framework and especially of the notion of an *organizational field* to a study of digitally mediated collective action (Pavan 2015), we have also highlighted its potentials in this regard. Namely, it allows us to overcome a naïve oversimplification of both *movements* and *networks*, by treating them as analytic categories rather than mere metaphors. In addition, the chapter has argued for a modification of Diani's original framework, by understanding the different modes as multiplex combinations of ties rather than discrete actor positions. In addition, the concept of *partial organization* (Ahrne and Brunsson 2011) has enabled us to conceptualize Facebook groups as one type of partial organization, in turn both allowing us to use frameworks designed to study interorganizational networks, as well as allowing us to distinguish between AAS-groups as informal, partial, or grassroots organizations, opposed to more formal organizations like parties. This allows us to additionally answer to a debate on the role of these formal organizations in various logics of collective action (Bennett and Segerberg 2013). This theoretical reasoning positions this thesis within scientific literature that studies "*how online networks, i.e. the systems of relations that emerge in the online space as a result of digital media use, contribute to the organization and* *the symbolic production of social movements*" (Pavan and Mainardi 2018:395). Thus, it is this thinking which leads us to a formulation of what we have termed research questions set III and set IV in chapter III-ii. These sets ask what *types* of ties are generated through the use social networking sites and how they can be read in terms of the dimensions of *boundary definition* and *resource exchange* which are the pillars of the MoC framework. As such, this approach operationalizes the reality of a multiplexity of different ties among actors and clearly goes further than many studies on online networks who relied solely on hyperlinks to measure the relations among (right wing) organizations (e.g. Caiani and Parenti 2013; Pavan and Caiani 2017). With this, my dissertation offers a novel and innovative, yet of course debatable, reading of social network data from a perspective of collective action scholarship. In addition, these research questions ask for the role of formal organizations in various types of AAS networks (i.e. Modes of Coordination), thus adding to the debate mentioned above and alleviating concerns about ignoring complex realities of collective action by focusing only on either parties as formal organizations or grassroots groups as informal organizations (Froio and Ganesh 2018; Haselbacher and Rosenberger 2018; Rucht 2018).

These observations and the research questions that follow in their wake had their main inspiration in theoretical debate. But also our second point of departure, namely the rise of right-wing activity in Germany, complemented to the research agenda of this thesis. It is important to note that studying AAS-groups is not like studying, for example, occupy wall street, the Arab spring, or other (by now) well-researched phenomena. Instead, as chapter III-i has shown, we are clearly witnessing a novel phenomenon, with new actors mobilizing on a relatively new topic in German society.

In addition, research on the far right from a collective action perspective still remains scarce, especially when it comes to their usage of social media (Caiani 2017). With this in mind, it is obvious that a thorough *exploration* of our case is important, in order to understand and describe it in the Weberian way. This is why the research questions in set I ask what AAS-groups can be identified in the first place and what their spatial and temporal activity patterns were. Thus, we opt to first survey our field, which according to Tilly "*include[s] spatial distributions of population or activity, but […] also include[s] temporal distributions and webs of interpersonal connections.*" (2004:214). Invariably, we start by identifying" *the actors that enter the space of the mobilization through services like Facebook, Twitter or YouTube*" (Pavan 2013:5), and move on to a thorough and theoretically grounded description of their activity patterns. In addition, the research questions in set II asked for the content that is produced by the written interactions of AAS-groups' members, the topics that are debated, their temporal change, and their potential to create collective identities of in- vs. outgroup. These questions flow both from the substantive interest to better understand and describe our case, as well as from a long-standing theoretical debate on identities and meaning production in collective action episodes (Benford and Snow 2000). Thus, our research design is one that combines insights from different scholarly debates with the curiosity in a novel phenomenon to an innovative exploratory design, firmly grounded in theory.

By now, I hope to have delivered a short recap of chapters I, II, and for the large part, chapter III. Before we move on to a short summary of the analyses in chapter IV, we can briefly highlight the data and the methodological tools that were used in these analyses. Building on existing research, journalistic accounts, and the work of left-wing watchdog organizations, we were able to identify a total 185 AAS-groups with public Facebook pages. For the purpose of data collection I wrote a script called Sammlr, which I made publicly available to any researcher (Hoffmann and Steimel 2018). At the time, it allowed researchers to collect, amongst other data, observations on activity, i.e. posts, comments, and reactions from these pages, together with a timestamp and, where applicable, the text of a message. Since we know of the importance of formal organizations and since existing research on German online right-wing networks has highlighted the role of right-wing parties (Caiani and Parenti 2013; Klein and Muis 2018; Pavan and Caiani 2017), we could also use Sammlr to add data on Facebook activities of the NPD and the AfD, the old and the new German right-wing parties. This, in total lead to a collection of almost 14 million observations – a massive amount of data to handle in a dissertation project with limited resources. Using the observations on AAS-groups allows to describe activity patterns across time and space, to study network structures with tools of social network analysis, as well as inspect content and meaning production with the help of structural topic models. Additionally, data on both parties allows to operationalize the role of formal organizations through a variable of party proximity for each AAS-group, in terms of their overlapping usership. To add to a more comprehensive picture of our case and see on- and offline activity as truly hybrid, I also collected data on offline AAS demonstrations, as well as attacks against asylum shelters. This involved working through the digital archives of the German Bundestag and identifying a total of 24 documents that could be used to track nearly 3,000 protest events related to asylum shelters, each coded for date and location. This process is documented in chapter III-iii of this dissertation.

Thus, equipped with a set of questions, a massive amount of data, and a methodological toolkit, we were able to conduct a number of analyses, presented in chapter IV. While it is not feasible to recollect every detail now, I would like to highlight some of the key findings from each section of that chapter and critically discuss them here.

In a first analysis in chapter IV-i, we have explored the phenomenon of AAS-groups and their protest activities, both across space and across time, using a triangulation of various data-sources. As I have argued above, this description of our subfield is a prerequisite step of the "*systematic network mapping*" (Diani 2015:5) that is the ultimate aim of this project. The research questions guiding this first analysis thus asked which AAS-groups can be identified, but also what their spatial and temporal activity patterns are and how these patterns correspond to a general interest in asylum-seekers and refugees and to records of offline AAS-activity. These questions are driven not only by the concern of identifying collective actors, but also by both substantive and theoretical concerns voiced in scientific debates. First, defining actors and their activities contributes to the growing scholarly literature on anti-asylum protests. As I have argued in this thesis, the wave of anti-asylum sentiments, protests, and violence is by far the biggest to hit German society since the early 1990s. As Dieter Rucht argues:

> *A catalyst for these developments were the slowly rising, then accelerating numbers of asylum seekers arriving in Germany. However, more important than the objective figures is their interpretation. To a greater extent than in the years around 1990, the influx of asylum seekers was now perceived as an immediate*

> *threat for the welfare, political stability and cultural identity of the German people* (2018:229).

Thus, a perspective focused solely on exogenous factors like influx of migration is dismissed in favor a scholarly lens focused on the actors that stage protest, their debates and narratives, and the structures that emerge in their interactions. In order to substantiate the claim of rising right-wing activity and understand its dynamics, a thorough collection and descriptive analysis is needed. I believe this thesis has provided a systematic approach of identifying collective AAS-actors on SNS, located and mapped their geographic scope, their temporal activity patterns, and tied these to independent data to substantiate the findings. In addition, the second important contribution of this analysis lies in the characterization of AAS-activity as a hybrid phenomenon between what is perceived as on- and offline. Unlike studies that were interested in finding (causal) effects of online on offline activity (e.g. Müller and Schwarz 2018), I have argued along the lines of studies which supposed that information flow depends on both on- and offline communication (Tufekci and Wilson 2012) and that online and offline protest often co-occur in the same place at the same time (Tilly and Tarrow 2015). Thus, this study was able to substantiate the findings of Vasi and Suh, who argued both the activity on SNS as well as street protest are caused by the more or less observable "*presence of energized activists*" (2016:150). Indeed, a look at the results of our analysis in chapter IV-i shows that both the presence and the activity of AAS-groups on Facebook generally correspond to the presence of street protest activity. In line with the findings by Rucht (2018), East Germany is at the center of protest activity, with the states of Saxony and Thuringia standing out, especially when we control for population size. As far as temporal patterns are concerned, we could again support existing findings of a correspondence of online and offline activity, although with different patterns for different activities. While public attention to refugees was virtually non-existing before the long summer of migration, both offline protest rallies and online AAS-activities were already ongoing at the time. We might thus assume that the influx of migrants and the public attention directed at it, likely did not *cause* AAS-activity but rather served as a *catalyst* for existing activity, much like Rucht (2018) assumes. It must be kept in mind, however, that this exercise was less interested in working out the exact relationship between online and offline activity and data, but rather offer a comprehensive account of the hybrid phenomenon under scrutiny. In addition, the triangulation with other data sources than Facebook served to corroborate our selection of AAS groups. In other words, if online and offline activity strongly correspond to each other, and we see little evidence of offline activity in areas and at times where we do not also find online activity, it is unlikely that we have missed any important cases. This is especially important in light of the problem of establishing construct validity using digital data that was designed for entirely different purposes (Veltri 2020). This does not mean we have established such validity, but that cross-referencing protest activity by means of independent sources of data (and types of activity) indeed indicates that we have likely captured anti-asylum-shelter protest in Germany. That being said, untangling the exact interplay between street and online protest might be well worth further inquire, yet is beyond the scope of this thesis. While surveying activists on their online and offline behavior with a questionnaire is surely viable option for this task, the possibilities of doing so in the clearly anti-scientific context of right-wing activists are severely limited. We can thus conclude that the empirical analysis corresponding to the questions in RQ-set I were both able to support our conceptualization of a hybrid sphere of mobilization and activity and our case selection of AAS-groups.

This allowed us to move on and inspect the actual textual content produced by members of AAS groups through their debates. The analysis in chapter IV-ii thus sought to answer the questions from RQ-set II, asking what topics could be identified in discussions among AAS-groups' members, how these evolved over time, and what collective identities were (re)produced through these messages. This was especially important given how little we knew about AAS-groups before. Thus, we were able to add a level of thick description to our case, by understanding what members of AAS groups talk about and how they talk about it. This could serve both to illustrate and to debunk the narrative of the "concerned citizens" coming from the political center of society. While there is ample evidence of latent racist and xenophobic attitudes across the political spectrum in Germany (Decker and Brähler 2018; Zick and Klein 2014), our analysis revealed a stark contrast between the depiction of the civilized, concerned, politically centrist self and the open hatred and insults that could be identified during the analysis. While it is not necessary to dive into the depth of exactly classifying right-wing populism or extremism for the sake of this study, it suffices to say that the topics identified throughout the content analysis in chapter IV-ii, rather point toward the political fringes than the center of society, exposing the frequent "we are not nazis" claim by AAS-protesters as a distraction strategy. Apologetic scientific accounts of more general anti-immigration protest, like Patzelt (2016, 2018), thus find little support in our data.

Theoretically, the analysis of topics in AAS-groups is driven by a long-standing interest in collective identities (Taylor and Whittier 1992) and collective action frames

(Benford and Snow 2000) in social movement research. The necessity of an all-encompassing collective identify has been questioned under the logic of connective action and its personalized framing, made possible by the affordances of digital media (Bennett and Segerberg 2013). While surely topics are a concept less elaborated (and more contested) than frames, we do not want to naively equate them with each other. Nonetheless, in a setting as homogenous as AAS-groups internal debates, we could see that topics can indeed resemble frames. The debates analyzed are not open discussions of issues in arena of debate, but rather serve to strengthen and foster clear narratives of problem definition and policy demands. For example, we could identify one topic on the impossibility of integrating Muslims into German culture. This is equivalent to a frame, as it clearly includes diagnostic elements that are classical to a framing perspective. Interestingly, Froio (2018) found exactly the same frame in her analysis of the extreme right in France.

Throughout the analysis, it was shown that the continuous framing of the self as the peaceful, modest, discourse-oriented, concerned average citizen, who is disadvantaged in comparison to migrants, is contrasted by several categories of “others”: On the one hand a lying press that seeks to deceive the German Volk about the true nature of asylum seekers, conspiring with the leftish political elite against the ordinary people. On the other hand, migrants and asylum seekers themselves, that are portrayed as sexual predators, unwilling and unable to assimilate into German mainstream culture. This clearly populist narrative of the average citizen versus the elite, was deeply enshrined with open hatred, racist, and violence, revealing of the true nature of AAS-protesters. The apparent contrast between a self-description as peaceful and reasonable and the hateful, violent, and sometimes criminal acts of speech by

AAS-groups, can be seen in light of "*motivated reasoning*" (Kunda 1990), where despite contrary facts, actors stick to a line of reasoning that supports their predisposition. Perceived threat (obvious for example in the prevalent "sexual violence" topic) is often associated with intolerance and "*motivated political reasoning*" (Crawford and Pilanski 2014). While our study does not seek to contribute to debates on misinformation or fake-news, we could nonetheless see that AAS-groups were active in promoting and reproducing dubious accounts of refugee violence, or conspiracy-theories of a great population exchange. Social psychologists have argued in this regard that this is a result of identity-protective reasoning:

> *Persons using this mode of reasoning are not trying to form an accurate understanding of the facts [...]. Instead they are using their reasoning to cultivate an affective stance that expresses their identity and their solidarity with others who share their commitments* (Kahan 2017:5).

An analysis of topic proportions over time further revealed that some shifts in proportionality are clear reactions to outside events, like protest events or instances of sexualized violence. Other topics, like demanding remigration or the clear anti-Islam nature of AAS-groups remained strong throughout the period observed. Thus, what we might witness in this instance is not citizens coming together to use social media as a forum for debate and openly develop a collective understanding of social phenomena, but more likely pre-existing frames being *catalyzed* through external events, as the logic of motivated reasoning would assume.

The following network analyses were surely the most innovative part of this dissertation, as they attempted to operationalize the MoC framework[84] using data from SNS. We could see that different types of interactions among AAS-groups and their members could be mapped to both mechanisms of resource exchange and boundary definition. This demonstrates that various actors make different use of the affordances offered by SNS, leading to different network properties, community constellations, and central actors. This answers to the theoretical claim of avoiding a fallacy to equate the presence of digital activity with collective action or treat the presence of social media in an episode of mobilization as a black box. Instead, we focused not on technology per se, but on "*what people do with what the technology 'affords' them and the structure this can create*", leading to analysis of "*how communication organizes action and what kinds of organization can result from different kinds of communication"* (Bennett and Segerberg 2013:9). This resonates with Diani (2015) and González-Bailón and Wang (2016), who argued that networks should not be treated as mere metaphors, but instead be subject to systematic empirical investigation. This perspective guided our theoretically grounded exploration of the various types of interactions, their potential meanings, and the structures that emerge from these actions. Through this examination, we found little support for the claim of a "*decentralized movement*" character (Schelter and Kunegis 2017) of German AAS-protests. Instead, we could see that a set of various core actors seemed to be central across the different types of networks under scrutiny, leading to network properties that are often found in online protest networks (González-Bailón, Borge-Holthoefer,

[84] Although, as we have discussed at different points in this dissertation, our operationalization clearly differs from Diani's (2015) original application.

and Moreno 2013). In addition, our theoretical perspective allowed to avoid a movement fallacy that would equate networks with social movements per se, but rather inquire the different MoC that emerge from patterns of repeated interaction among informal organizations. It could be shown that an additive combination of ties in the two dimensional framework of MoC leaves only a small amount of groups connected in the largest component of the network that is constructed of social movement ties, characterized by strong interaction in terms of both boundary definition and resource exchange. Thus, it was our adaption of the framework from a positional focus toward a focus on ties that allowed to compare different Modes of Coordination in light of the different networks that emerge from each mode. This move helped us to substantiate some expectation on the networks that might be produces by operating in one mode or another. It could thus be shown that a social movement mode of coordination is far from the default, but where this type of tie exists, it also produces the densest of our networks, supporting claims about the cohesive nature of this type of network (Baldassarri and Diani 2007). In contrast, far more ties resembled the organizational and coalitional modes of coordinating collective action, meaning that different mechanisms are at work, rather leading to a loose integration of many actors through occasional or even sustained cooperation, than to sustained ties of solidarity.

What this means is that there is clearly no technological determinism leading to one type of interaction or to specific network properties, but rather that very different structural patterns emerge from different types of interactions. When we look at our field of AAS-groups through the lens of MoC, we can thus see that platform affordances are used very differently, showing a diverse range of interactive patterns. Neither can we support claims of mindless “clicktivism” that leads to overly dense networks without meaning, nor could we support overenthusiastic assumptions about technology leading to a movement-character of collective action per se. Instead, our understanding of different types of interactions in terms of resource exchange and boundary definition allowed to draw a nuanced picture, that showed actors' strategic interests and choices when they enter the digital space of coordination and mobilization. Thus, we were able to show how the MoC framework can help us illustrate and entangle the various mechanisms at work and how they relate to network structures.

In chapter II, we have argued for an adaption of the original framework, shifting focus away from actors' positions and how these are matched by actors' properties toward an understanding of MoC as types of ties that allow each group to be involved in multiple modes at the same time. Thus, our exercise could highlight the crucial aspect in multiplexity in two ways: First, Modes of Coordination are multiplex in the sense that each mode reflects a combination of different ties of resource exchange and boundary definition. And second, we can understand that a field of AAS-groups is tied in a multiplex network, where different MoC are expressed simultaneously through different types of ties, albeit with different alters, and with different engagement.

In addition, through the application of exponential random graph models, we could highlight significant differences in the group-level predictors for ties in each mode. This was specifically important in shedding empirical light on the theoretical debate regarding the role of formal organizations, that varies according to the different logics of collective and connective action (Bennett and Segerberg 2012, 2013). It was shown that beyond the well-known phenomenon of local clustering (Mislove et al. 2007; Pavan 2017) and activity, actors' proximities to formal organizations of the political right do indeed explain tie formation, although differently for the different ties and the different parties. We found that groups with a higher affinity to the National Democratic Party were especially able to activate ties of both weaker and more intense resource exchange. Likewise, those with a higher affinity to the Alternative for Germany, which Rucht classified as a "*social movement party*" (2018:235), were also more able to activate ties that involved both more intense resource exchange and more intense boundary definition. Thus, the MoC framework could be applied to both distinguish different modes and to show that the role of formal organizations in this instance of protest-mobilization seems to point toward a more classical logic of collective action, rather than the personalized logic of connective action. Indeed, bringing these different concepts together in a comprehensive perspective can help us to more systematically assess the role of SNS in collective action phenomena and differentiate between various constellations of ties and the actors that are involved in these.

However, like any scientific endeavor, this dissertation faces some limitations that need to be addressed to point to way for further inquiry. Firstly, we must highlight the constraints of a single-case study, that does not allow for comparative evaluation of the findings. While this might greatly improve generalizability and put results into context, it is simply beyond the scope of this dissertation. Instead, the contribution of this thesis was focused in the comprehensive and systematic theory-driven analysis of a novel dataset, proposing an innovative approach as a starting point for further research rather than a definitive answer to the challenges that come with it. Nonetheless, we can briefly sketch out a research agenda that could address this limitation. This would lead us to ask what comparative dimensions might be worth exploring to solidify and contextualize our findings. Of course, a study on right-wing actors invites the comparison with their political antagonists. Such a comparative approach would allow us to understand the specifics of right-wing organizations as opposed to the political left. This provides an especially worthwhile avenue, as previous research has found "*divergent left-right preferences for political engagement, organization, and communication*" (Bennett, Segerberg, and Knüpfer 2018:1655). However, a mere comparative design of left-vs.-right activity on an issue like migration cannot ignore the likelihood of reaction and interaction between opposing camps[85]. Thus, based on our findings and theoretical reasoning, we could formulate working hypotheses that would argue for less importance of the proximity to formal organizations on the pollical left, due to their different stance toward political parties. Also, a longer tradition of collective action on that side might facilitate the formation of social movement ties. Methodologically, this would challenge us to not only consider coordination and mobilization among actors of a field, but also incorporate the relevance of *signed* ties in such a design. In other words, we must expect actors on one side of the political spectrum to be aware of their counterparts and very likely hold negative relations to them, such as clashes, counterdemonstrations, or providing and revealing negative information. Whether we would consider a "shared dislike" of specific opponents a boundary defining tie in terms of MoC and/or look at a network of negative relations explicitly, would surely be the important considerations in such an "issue-based" comparative design. In principle, our selection of data would be appropriate for such a design, given additional qualitative interpretation, for example

[85] Something many studies of collective action, including this one, must be accused of.

whether protest events in the co-mobilization network are of the "counter-demonstration" type or not.

Of course, these considerations on comparative research designs intersect with the second major limitation of our design: The focus on a broad picture of the structures of interaction among AAS-groups was favored over a dynamic model of tie formation (and dissolution), that would have given more room to explaining the various mechanisms of coordination and to the question if and how ties of either type precede or follow other types. For example, do ties of the coalitional type evolve into the social movement type? How stable are these networks over time? How do networks look in times of low or high mobilization? Among others, McAdam, Tarrow, and Tilly (2004) have explicitly argued for a dynamic perspective to understand contention. In addition, our debate on the different logics of collective or connective action (Bennett and Segerberg 2013) would be enriched by a perspective that could inform us whether the influence of formal organizations on tie formation in any mode is subject to temporal change. We can easily formulate two opposing working hypotheses, namely that the importance of formal organization is higher in the initial phase, when organizational resources are crucial in establishing networks and building cooperation. On the other hand, we can hypothesize that in later stages, the influence of formal organizations is even higher, as contentious actors have realized political opportunities and found their "political home". As all of our data on activity, except page likes, is timestamped, such an analysis would be able with the data at hand. Methodologically, this would involve slicing our networks into discrete episodes, maybe based on some external criteria, and repeating our existing analyses, or relying on sophisticated models like temporal ERGMs.

Thus, we can see that the present work lends itself well to further inspection, by allowing us to generate additional questions and expectations that can be tested with the data at hand. For now, however, we will have to lay this study's limitations to rest, and conclude that the exploratory nature of this study has advanced both theoretical debate and substantial knowledge through a comprehensive analysis of activity patterns, content production, and networked interactions of contentious actors on the political right.

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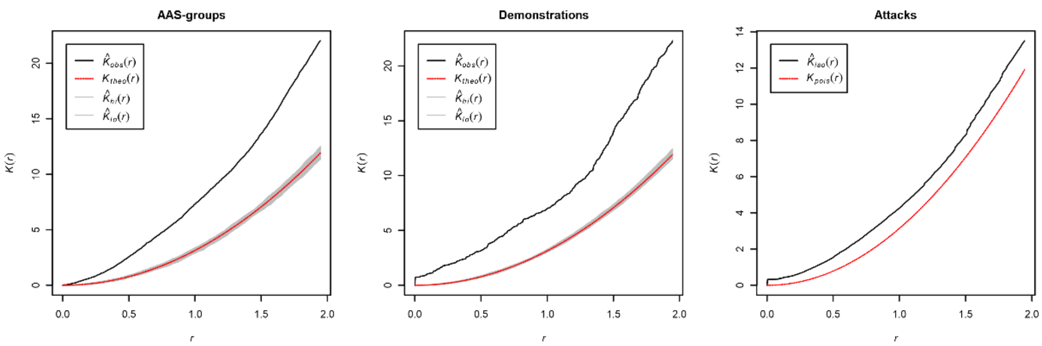
Appendix

Figure A.1 K-function test results for the spatial distribution patterns of AAs-groups (n=185), demonstrations (n=276) and attacks against asylum shelters (n=2,526).



Note: The red lines indicate the test statistic for a spatially random distribution of an equal number of points. For AAS-groups and demonstrations, we could run 49 simulations, for attacks this was not feasible due to the computational intensity.

Figure A.2 Geographic kernel densities of AAS-groups (n=185), demonstrations (n=276), and attacks against asylum shelters (n=2,526).

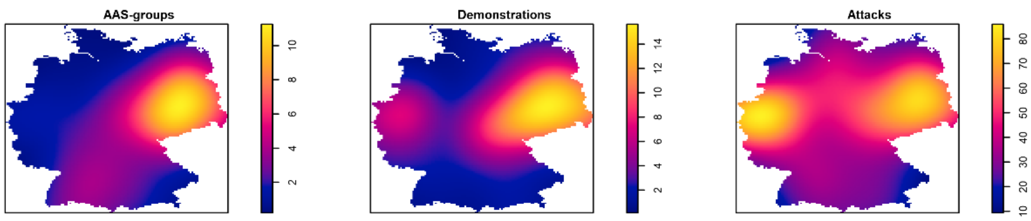


Figure A.3 Time and peak value (log scaled) of each AAS-groups' activity peak, along with groups' total activity count (size) and the average activities per active day (color). Lines represent 2D-density.

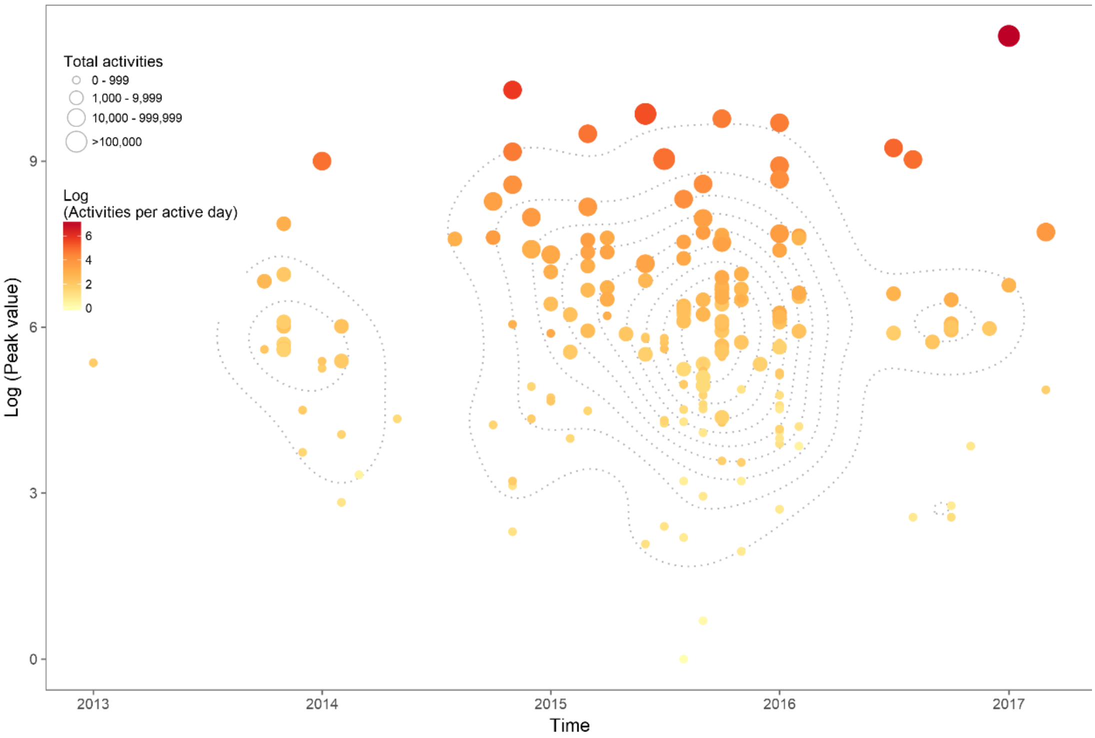


Figure A.4 Diagnostics of the empirical model fit for Structural Topic Models for different numbers of Topics.

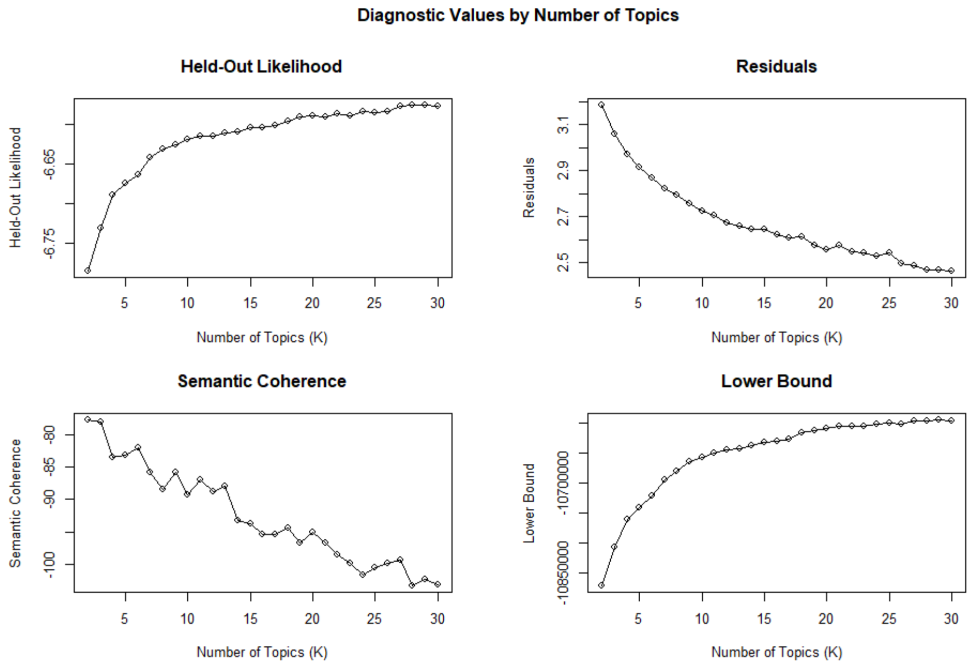


Figure A.5 Histograms of Document-Topic-Probabilities for 13 topics and 55,297 documents, including means (purple line).

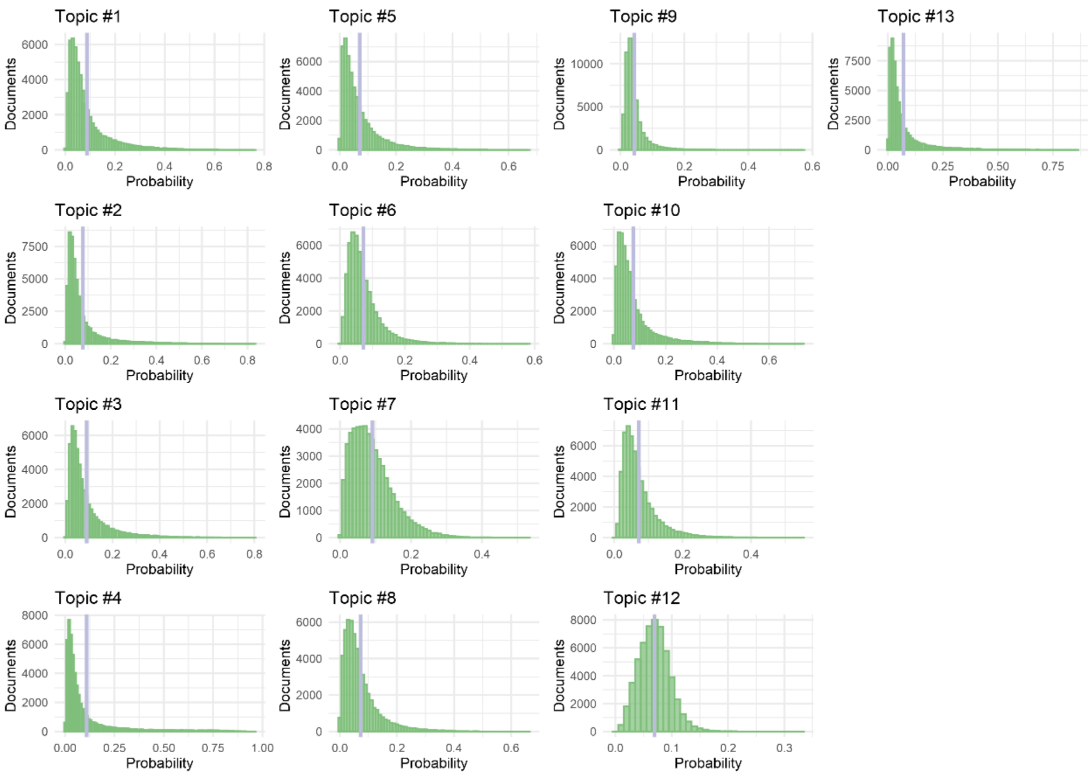


Figure A.6 MDS layout of the recognition network (communities of size > 8 are colored)

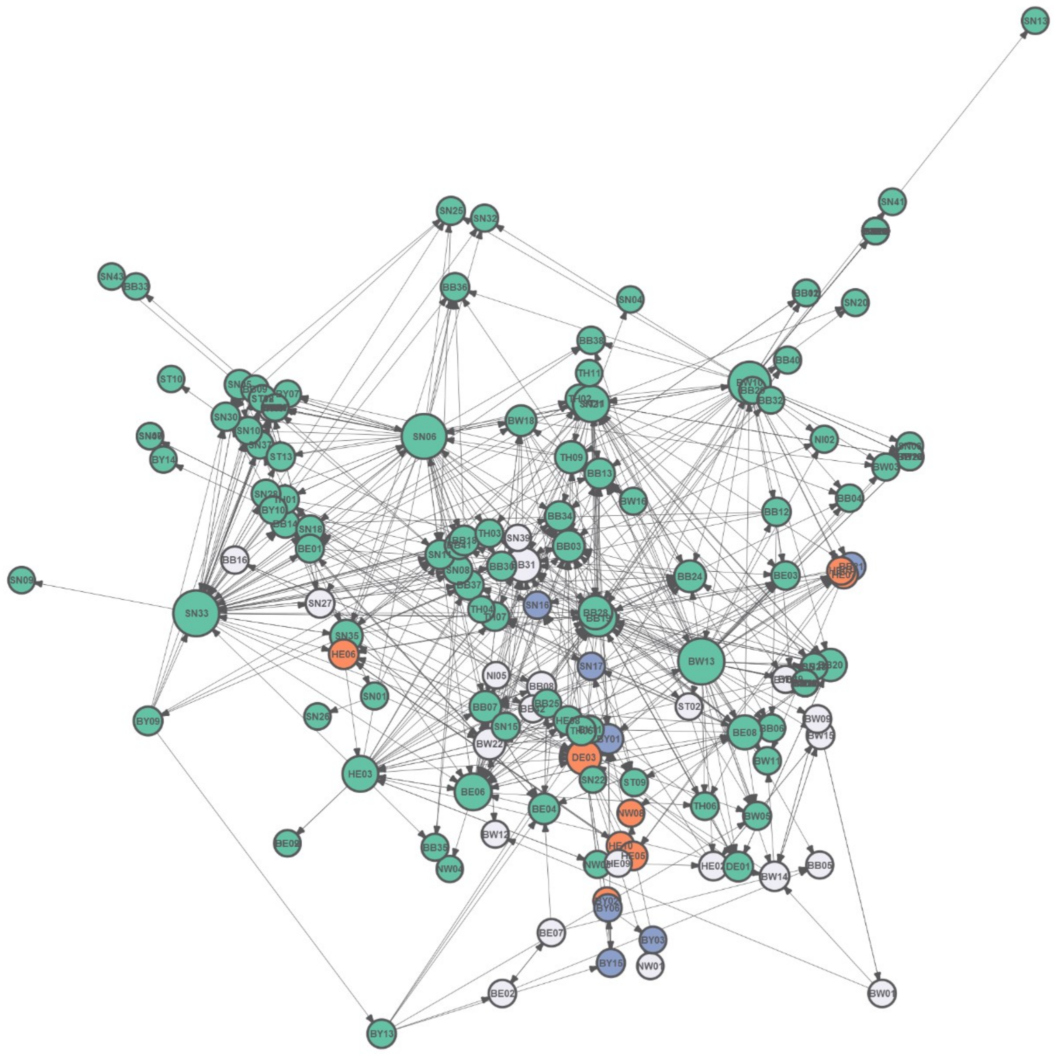


Figure A.7 MDS layout of the information sharing network (top eight communities are colored)

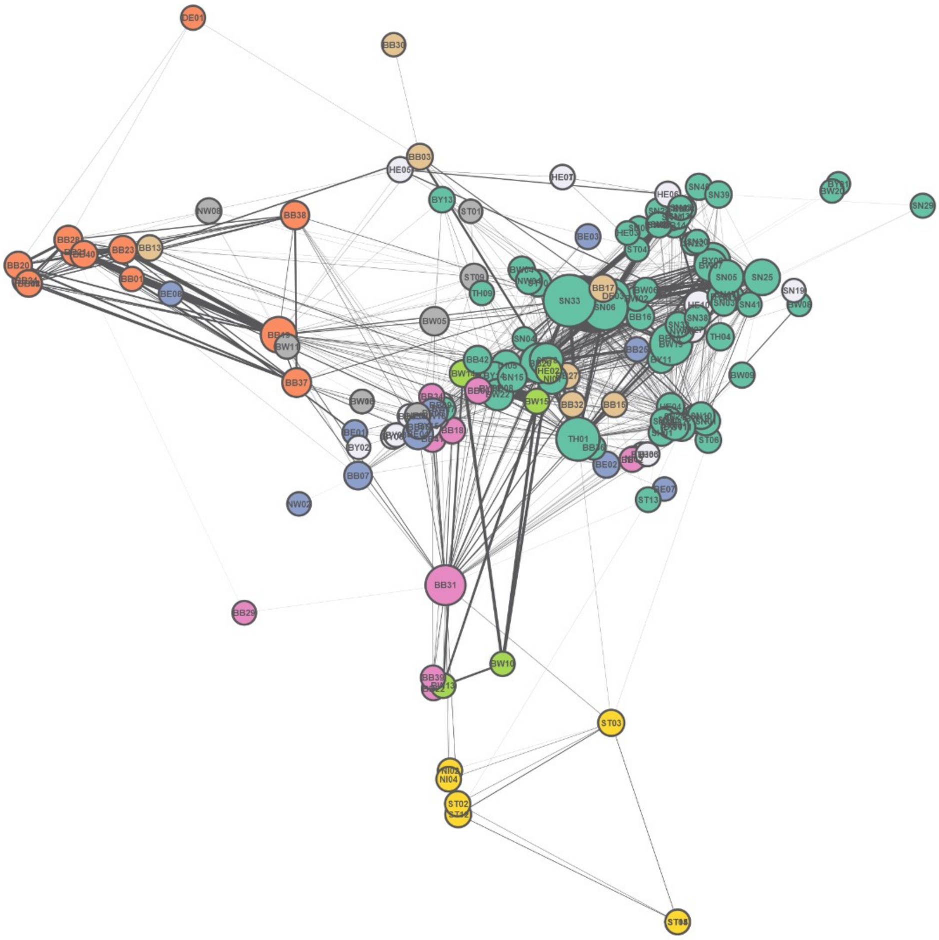
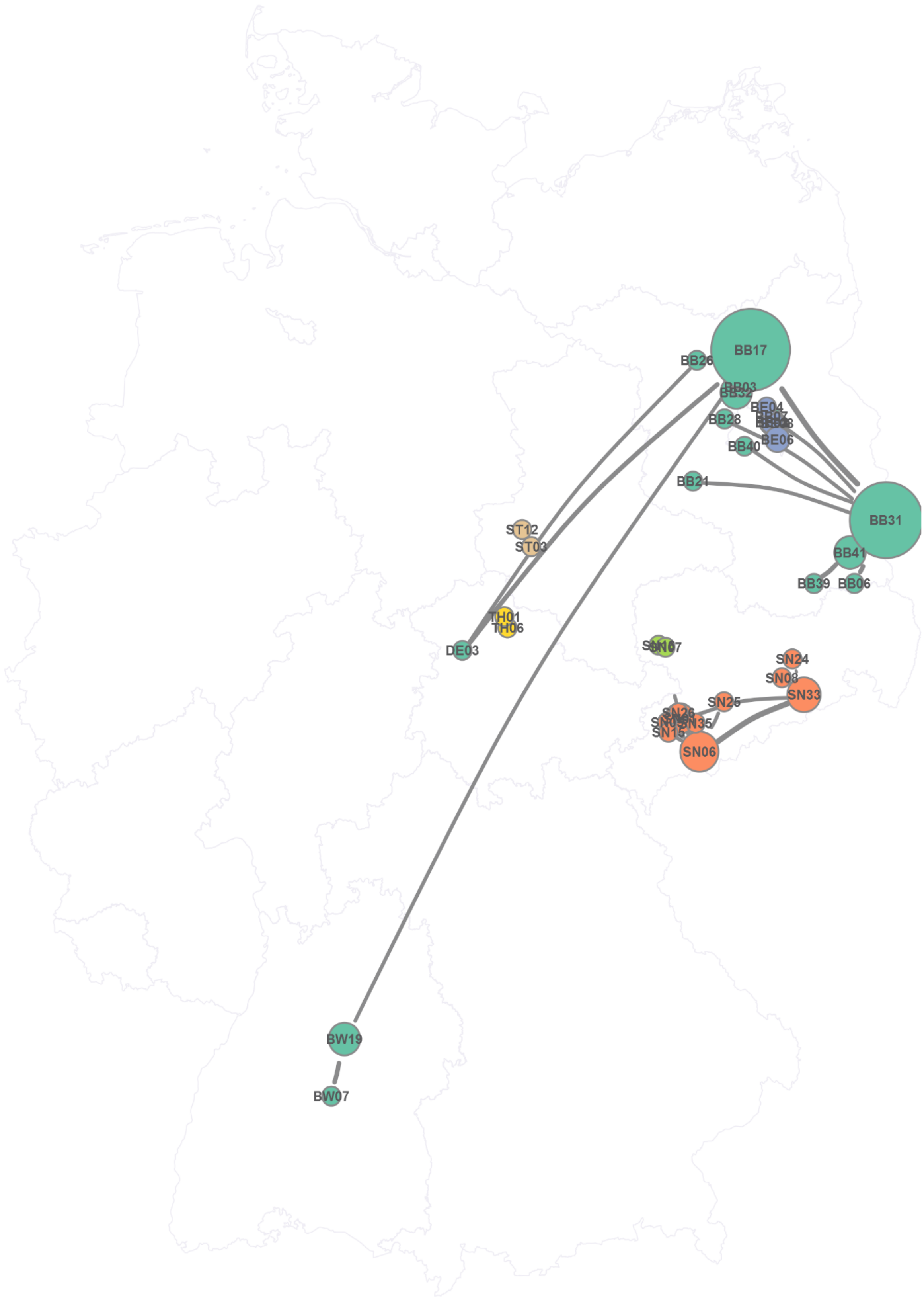


Figure A.8 Geographic Layout of the co-mobilization network (components colored)



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