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Conspiracy Theory Networks on Twitter

A Social Network Analysis among Conspiracy Theorists

submitted by

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[redacted]

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Contents

1 Introduction

The Covid-19 pandemic is currently giving rise to a number of conspiracy theories that are attracting a lot of public attention. However, conspiracy theories have been around for a long time and are not an exclusive phenomenon of modern times. The belief that witches cause natural disasters and illness among people goes back to the Middle Ages, led to the witch hunts and can be understood as a conspiracy theory popular at the time. Another conspiracy theory from more recent times, but even before the Internet, is the belief that the U.S. faked the moon landing. However, with the advent of the digital age and social media, the reach of conspiracy theories has broadened, and distant people with the same beliefs have been given the opportunity to interact with each other. Whether this has led to an increase in conspiracy beliefs is another topic worthy of discussion, but it has definitely increased the visibility of conspiracy beliefs. An example of the spread of conspiracy theories in public discourse is the candidacy and presidency of Donald Trump. To find an example of Trump's flirtatiousness with conspiracy theories, one does not have to look far: In a white house press conference Trump referred to the U.S. State Department as the "deep state department". What could be mistakenly dismissed as a harmless joke runs like a thread through Trump's political career. From his slogan "drain the swamp" used during his candidacy[1] to his political attacks on the opposition, the conspiracy narrative has always played a role. Since then, the research interest in conspiracy theories has expanded and the dissemination of conspiracy theories in social media has become a relevant object of research.

This thesis focuses on the analysis of conspiracy theories on Twitter and in particular on the way users sharing conspiracy related information form social networks. In the literature review of this thesis, the motives and predispositions of people who hold conspiracy beliefs and the possible effects of these beliefs are first summarized from a psychological perspective. Then the general spread of conspiracy theories with regard to information diffusion is discussed. In order to analyze conspiracy networks on Twitter, the theoretical framework of this thesis is based on network theory and the concept of opinion leadership. By combining both previous findings and established theories from social network research, the research question of this thesis is summarized in a concluding argument before the data collection process and the methodological approach are explained. After presenting the results of this thesis, the main findings are

[1] Although Trump did not invent this term, his extensive use of the term in connection with the elimination of corruption implied to some extent a government conspiracy.

discussed and related to previous research.

2 Misinformation, disinformation and conspiracy theories

When discussing conspiracy theories, one should first be clear about the term 'conspiracy theory'. Especially since current research has popularized several terms that all describe overlapping phenomena. Besides the term 'conspiracy theory' researchers also often use the terms 'misinformation' and 'disinformation'. Since the definitions are varying and up to this point there is no broad scientific consensus on them (Tucker et al. 2018, p. 55), it is very important to discuss and distinguish between these terms.

Starting with the term 'misinformation' multiple authors proposed multiple slightly differing definitions. Born & Edington (2017) define misinformation as "unintentionally promulgated, inaccurate information" (Born & Edington 2017, p. 4). The main defining characteristics being that misinformation is communicated without any intent to manipulate, mislead or deceive people and that it is objectively false. Benkler et al. (2018) uses a similar definition with the small addition that misinformation is communicated "without meaning to be wrong" (Benkler et al. 2018, p. 24). This is an important addition and raises an even more important question. What about false information that is disseminated with a specific intention? The intention of the communicator plays a decisive role in this debate, because certainly not all false information is spread unintentionally. Benkler et al. (2018) define information that is "manipulating and misleading people intentionally to achieve political ends" as 'disinformation' (Benkler et al. 2018, p. 24). The main differences in contrast to misinformation lie here in the intention to deceive and "known falsehood" (Stahl 2006, p. 86) of the information. The term 'disinformation' gained popularity especially in relation to the term 'fake news'. Fake news could be understood as a subcategory of disinformation, since they have the same characteristics, being deliberately manipulative and spreading false information[2]. Moreover, fake news tries to appear as credible news (Tandoc et al. 2017, p. 11), which might further increases the effect it has on the reader. In the 2016 U.S. elections in particular, fake news and thus disinformation played a major role and led to extensive discussions about the influence of fake news (see Bovet & Makse 2019, Allcott & Gentzkow 2017).

[2]For a more in-depth definition of the therm 'fake news' see Tandoc et al. (2017)

But how does the term 'conspiracy theory' relate to misinformation and disinformation and what distinctions can be made between these terms? Tucker et al. (2018) proposes that conspiracy theories might be defined as "false stories repeated over time with known contrast to receive wisdom, [which] includes reference to fact that other are trying to suppress the truth" (Tucker et al. 2018, p. 55). Other definitions prioritize the conspiracy more. Sunstein & Vermeule (2009) define a conspiracy theory as "an effort to explain some event or practice by reference to the machinations of powerful people, who attempt to conceal their role (at least until their aims are accomplished)" (Sunstein & Vermeule 2009, p. 205). Oliver & Wood (2014) and Douglas et al. (2019) use similar definitions, referring to a secret group that controls significant events and social developments while pursuing their own goals. As opposed to the definition proposed by Tucker et al. (2018), these definitions do not necessarily claim that conspiracy theories rely on false information that is repeated over time, and therefore do not necessarily have to be false. It is important to say that not all conspiracy theories in this sense should be disregarded as "unjustified or unwarranted in all imaginable situations or societies" (Sunstein & Vermeule 2009, p. 209). Given the political and societal situation, conspiracy theories are not always as unlikely as they seem. In fact, some conspiracies have turned out to be true, with the Watergate Affair being one of the most prominent. It is also very important to use these terms carefully. Some researchers argue that the term can be used to deny people their credibility by referring to them as 'conspiracy theorists', which renders any arguments of the alleged conspiracy theorists untrustworthy (see Husting & Orr 2007). It is a simple and manipulative way to fend off any criticism (Douglas et al. 2019, p. 5). Nevertheless, within the framework of this thesis the emphasis should be placed on conspiracy theories that are most likely false and based on misinformation and disinformation. That many common conspiracy theories are highly improbable can be shown by mathematical models that calculate how likely it is that a conspiracy will be uncovered (see Grimes 2016).

For this thesis the following working definition by Douglas et al. (2019) shall be used:

> "Conspiracy theories" are attempts to explain the ultimate causes of significant social and political events and circumstances with claims of secret plots by two or more powerful actors (Douglas et al. 2019, p. 4)

3 Defining the field of research

After defining the object of research of this thesis, the next step is to define the research field. The research interest within conspiracy theories is closely related to the people who believe in conspiracy theories. As with any idea or information, beliefs do not just appear in people's minds by chance. They are spread through communication. With the rise of social network sites it became incredibly easy for people to share their thoughts, express their beliefs and connect to like-minded people. It has also become much easier to reach massive audiences without having to pass a gatekeeper in the classical sense. As Tucker et al. (2018) note, ordinary people now play an "active role" in disseminating political information online, while also consuming news on social media (Tucker et al. 2018, p. 17). Therefore these websites themselves became interesting research objects. If one considers the U.S. election in 2016, the influence of everything that happens online becomes even more apparent. Especially with regard to conspiracy theories Donald Trump's candidacy is relevant. He often revealed his belief in various conspiracy theories and even used them during his presidency to reject criticism or attack political opponents (Benkler et al. 2018, p. 18). His main means of communication is the social media platform Twitter. The platform not only allows Trump to communicate directly with his followers, but also allows him to inject him and his tweets into the traditional news agenda (Benkler et al. 2018, p. 19). Twitter itself is playing an increasingly relevant role in political discourse. Just like other social networking sites, it is "an important source of political information" (Southwell et al. 2018, p. 143).

Because of Twitter's relevance in political and public discourse, Twitter was chosen as a platform to be researched. Another reason to prefer Twitter over other social media platforms when it comes to analyzing social networks online is the fact that the data is easily accessible and rich in information. This is both a curse and a blessing. While data is easily accessible and therefore enables research by scientists with limited resources, it also means that most research on online social networks is based on Twitter data. When discussing bot detection methods and why most current models focus on Twitter, Tucker et al. (2018) argue that besides the importance of Twitter in political discourse, its "easy-to-use API" and the lack of alternatives explain why most research has focused on Twitter up to this point (Tucker et al. 2018, p. 35f). After the data privacy scandal around Cambridge Analytica, Facebook restricted access and functions of their API (see Facebook 2018) which made it very complicated for researchers to access Facebook data.

The final reason to mention why Twitter was chosen, especially in the context of

investigating conspiracy theories, is that prior research suggests that "conspiracy beliefs can be increased even when conspiracy cues are subtle and implicit" (Lyons et al. 2018, p. 8). This indicates that even small fragments of information, such as tweets, can influence and promote conspiracy beliefs.

4 Literature review

4.1 Believing in conspiracy theories

The belief in conspiracy theories among the population is fairly high. In the U.S. around half of the population believes in at least one conspiracy theory (Oliver & Wood 2014, p. 964). Hasty claims that the irrationality or intelligence of these people are to blame should be disregarded. Researchers have many different theories about the main reasons why people believe in them. But what conspiracy theories do people actually believe in? One of the conspiracy theories popularized by Trump, among others, was the claim that Barack Obama was not born in the U.S. and does not have a legitimate birth certificate (Benkler et al. 2018, p. 18). The resulting "Birther" movement demanded that Obama had to prove his citizenship in order to run for president. And even after his birth certificate was released, 13% of the American population still doubted that Obama was an American citizen (Gallup 2011). This example illustrates an important feature that all conspiracy theories have in common. Even though clear evidence has been published to refute the claims of the "Birther" movement, some followers hold on to their beliefs. Sunstein & Vermeule (2009) claim that conspiracy theories have a "self-sealing quality" that makes them very resistant to correction (Sunstein & Vermeule 2009, p. 207). A study by Nyhan & Reifler (2010) shows that people who are misinformed, which includes people who believe in conspiracy theories, are in fact more resistant to corrective information and continue to believe in their misperceptions. Corrections not only "fail to reduce misperceptions [...][,] even worse, they actually strengthen misperceptions" (Nyhan & Reifler 2010, p. 323). However, some empirical studies have shown that this 'backfire-effect' probably does not exist (Wood & Porter 2018) and that corrections still might work (Lyons et al. 2018, p. 5). Lyons et al. (2018) assume that the effectiveness of corrective information probably depends on the person or institution communicating the correction, the time of publication of corrective information, and how long a person has believed in a conspiracy theory (Lyons et al. 2018, p. 8f). This illustrates that it is very difficult to disprove the belief in conspiracy theo-

ries, making it all the more important to understand why people believe in conspiracy theories at all. This question will be answered in the next two sections.

4.1.1 How widespread are conspiracy theories?

As mentioned at the beginning of the previous section, about 50% of the U.S. population believes in at least one conspiracy theory. Although much research has focused on American citizens, believing in a conspiracy theory is not a phenomenon limited to the U.S. Referring to data collected by YouGov in 2015 and 2016, Drochon (2018) shows that conspiracy belief is even slightly higher in the UK: 55% of the population believes in at least one conspiracy theory (Drochon 2018, p. 3f). A comparison of six European countries with the U.S. showed that "among all countries at least half of the population believes in at least one conspiracy theory — thus making the Europeans as likely to do so as the Americans" (Drochon 2018, p. 8). However, significant differences between the countries became apparent when comparing the belief in conspiracies in Sweden and Portugal (Drochon 2018, p. 7f).

There are multiple conspiracy theories, even some that contradict themselves. Wood et al. (2012) conducted two studies, both of which indicate that believing in several conspiracy theories does not necessarily mean that these conspiracy theories must support each other. In one of them, for example, they were able to show that the belief that Princess Diana faked her death correlated positively with the belief that she was murdered (see Wood et al. 2012). Apart from this, there are many people believing in multiple conspiracy theories. In the study conducted by Oliver & Wood (2014) half of the participants who agreed with at least one conspiracy theory actually agreed with two or more conspiracy theories (Oliver & Wood 2014, p. 957).

In summary, conspiracy theories and the belief in conspiracy theories are widespread among the population, but depending on the conspiracy theory, the belief in conspiracies varies from country to country. While it is very complicated to explain why belief in conspiracy theories varies across countries, it is easier to explain why some people believe in conspiracy theories and others do not. This question will be examined further in the next section.

4.1.2 Who believes in conspiracy theories?

To understand the spread of conspiracy theories on which this thesis focuses, it is important to begin understanding why people believe in them in the first place. Douglas

et al. (2019) claim that there are three central motives why someone might believe in a conspiracy theory: epistemic, existential and social.

Epistemic motives consist mainly of the general need to find meaning in a world perceived as random and to find explanations for events that coincide with personal beliefs. This motive probably applies to almost everyone in the world, but becomes a motive to believe in a conspiracy theory when other factors apply. Sunstein & Vermeule (2009) argue that believing in a conspiracy theory is often the result of a "crippled epistemology" (Sunstein & Vermeule 2009, p. 211) and is not due to irrationality but a lack of information. Douglas et al. (2019) claim that conspiracy theories appeal to those who seek meaning, but "who lack the cognitive tools or experience problems that prevent them from being able to find accuracy and meaning via other more rational means" (Douglas et al. 2019, p. 8). Other motives for believing in a conspiracy theory could be existential ones. People with little faith in the political system and a feeling of being excluded from society may turn to conspiracy theories to satisfy their existential needs (Douglas et al. 2019, p. 8). In this case, however, it is not the conspiracy theories that are to be regarded as a problem, but rather the condition in which these people find themselves. The last motives that Douglas et al. (2019) identify are social motives. It is within the framework of this thesis that the social motives might be the most interesting. Some research suggests that the appeal of conspiracy theories stems from the feeling of receiving "rare, important information that other people do not have" (Douglas et al. 2019, p. 9), which can ultimately push the ego and increase self-esteem. Another motive unfolds when a group to which an individual belongs feels "undervalued, underprivileged or under threat" (Douglas et al. 2019, p. 9). Since people generally want to have a positive relationship to the groups to which they belong, this can quickly lead to "collective narcissism – a form of ingroup positivity that reflects a belief in the ingroup's greatness associated with a conviction that others do not acknowledge the ingroup's worth enough" (Douglas et al. 2019, p. 9). This strong ingroup positivity and the desire to distinguish themselves from other groups could possibly be observed in dense network clusters. Other motives to believe in conspiracies could be a consequences of previous discrimination. Individuals or groups who have faced discrimination by a dominating group "are more likely to believe in conspiracies directed at their own group" (Douglas et al. 2019, p. 9).

Apart from these three motives, researchers also focused on identifying predispositions that may influence the belief in conspiracy theories. One of the earlier studies, which dealt with conspiracy theories and the predispositions determining belief in

them, was conducted by Goertzel (1994). Besides stating that belief in conspiracy theories is correlated "with anomia, with a lack of trust in other people, and with feelings of insecurity about unemployment" (Goertzel 1994, p. 738f), he argues that these beliefs fit perfectly into a "monological belief system" (Goertzel 1994, p. 740) and provide a simple and quick explanation for events that might threaten the belief system. From this he concludes that "the more conspiracies a monological thinker believes in, the more likely he or she is to believe in any new conspiracy theory which may be proposed" (Goertzel 1994, p. 740). Further evidence for this hypothesis was provided by Swami et al. (2011) who were able to show that "the strongest predictor" for believing in a conspiracy theory is believing in other conspiracy theories (Swami et al. 2011, p. 452). The argument of the 'monological belief system' was later challenged by the aforementioned study by Wood et al. (2012). The authors conclude "that the monological nature of conspiracism [...] is driven not by conspiracy theories directly supporting one another but by the coherence of each theory with higher-order beliefs that support the idea of conspiracy in general" (Wood et al. 2012, p. 771).

The discussion about predispositions has since been split up into two research topics: political predispositions such as partisanship and conspiratorial predispositions (Uscinski et al. 2016, p. 59). With regard to conspiratorial predispositions, Oliver & Wood (2014) suspect that not the belief in other conspiracy theories is a strong predictor, as Swami et al. (2011) claims, but more precisely a series of psychological predispositions (Oliver & Wood 2014, p. 954f). Later on, they were able to show that people who believe that "unseen, intentional forces exist and that history is driven by a Manichean struggle between good and evil" (Oliver & Wood 2014, p. 964) have a significantly higher agreement in all tested conspiracy theories than people without these predispositions. A study by Bensley et al. (2019) provides similar results, showing that generic conspiracist ideation correlates strongly positively with a belief in (false, unsubstantiated) conspiracy theories (Bensley et al. 2019, p. 10). But these predispositions do not predict belief in all kinds of conspiracy theories. Uscinski et al. (2016) note that in case of the belief in a climate change conspiracy, the strongest predictor is not conspiratorial predispositions, but Republican partisanship (Uscinski et al. 2016, p. 68). This suggests that not only conspiratorial predispositions can influence conspiracy beliefs, but also political predispositions. Douglas et al. (2019) note that conspiracy theories that are consistent with someone's personal political ideology are more likely to be adopted than conspiracy theories that represent a divergent political ideology (Douglas et al. 2019, p. 11). But not all conspiracy theories necessarily refer

to a particular political ideology. Oliver & Wood (2014) found that in the case of the chemtrails conspiracy theory and a fictitious conspiracy theory invented by the authors, neither liberals nor conservatives tended to agree or disagree with either one (Oliver & Wood 2014, p. 957f). In the case of 'ideological' conspiracy theories, "conservatives are more likely to agree with the Soros and Birther conspiracies" (Oliver & Wood 2014, p. 961), two conspiracy theories that suspect political opponents (for example, Democrats) of conspiracy. These findings are consistent with Uscinski et al. (2016) who found that partisanship plays a central role in the adoption of a certain conspiracy theory if "the conspiracy theory has a partisan element" (Uscinski et al. 2016, p. 68).

In summary, it can be said both conspiratorial and political predispositions influence belief in conspiracy theories. If a conspiracy theory contains an ideological element, political predispositions outweigh conspiratorial predispositions in their influence (Uscinski et al. 2016, p. 65f). The main argument to be made here is that people who believe in one conspiracy theory are more likely to believe in other conspiracy theories. Whether it is due to their political or conspiratorial dispositions varies from case to case, as the different results of several studies show (see Douglas et al. 2019, p. 11).

4.2 The effects and spread of conspiracy theories

As discussed in the previous sections, conspiracy theories are widespread and quite popular among the population. But why should researchers be interested in conspiracy theories anyway? As Southwell et al. (2018) and Sunstein & Vermeule (2009) say, spreading misinformation does not necessarily have to be malicious in every case. The same applies to conspiracy theories. Sunstein & Vermeule (2009) note, the conspiracy theory held by children that a mysterious "Santa Claus" distributes presents all around the world on Christmas, although a false theory, is not dangerous (Sunstein & Vermeule 2009, p. 206). But many conspiracy theories can be. Researchers investigated the effects of various conspiracy theories and in most cases there were serious consequences. The World Health Organization metaphorically described the inaccurate and false information circulating about the coronavirus as an "infodemic", which shows that conspiracy theories may resemble diseases in some aspects (WHO 2020, p. 2). And similar to diseases, conspiracy theories spread partly through human interaction.

In the next two sections, the significance of this thesis is demonstrated by listing the consequences of conspiracy theories and examining the spread of conspiracy theories.

4.2.1 What are the effects of (believing in) conspiracy theories?

The recommended vaccination coverage in the population to ensure herd immunity is 95% or higher, as recommended by the WHO (Muller et al. 2007, p. 4f). However, in 2018, an estimated 19.4 million children under one year of age are still not receiving any vaccination (see WHO 2019). And while many of these children come from developing and emerging countries and may not have proper access to health care, there are also people who choose not to vaccinate themselves and their children. Researchers have since tried to find out where this 'vaccination hesitation' comes from (see Dubé et al. 2014). Part of the problem in many cases, among other factors, is the belief in an anti-vaccine conspiracy theory. These theories link vaccinations to serious consequences such as autism and sudden infant death syndrome and claim that the government and pharmaceutical companies are hiding these consequences. Although many of these claims are not scientifically tenable (see for example Taylor et al. 1999), many people believe in them. In a study by Jolley & Douglas (2014) the authors examined the consequences resulting from these beliefs. They found that believing in anti-vaccine conspiracy theories correlates negatively with the intention to vaccinate (Jolley & Douglas 2014, p. 3). By establishing a 'pro-conspiracy', an 'anti-conspiracy" and a control setting, Jolley & Douglas (2014) were also able to show that the vaccine intention was significantly lower in the 'pro-conspiracy' setting (Jolley & Douglas 2014, p. 6). Another study on this topic by Lyons et al. (2018) shows that exposure to anti-vaccine conspiracy theories, which the 'pro-conspiracy' setting basically did, did not reduce the intention to vaccinate (Lyons et al. 2018, p. 8). On the topic of conspiracy beliefs about HIV, Bogart et al. (2010) conducted a study on the connection between conspiracy beliefs and non-adherence to HIV therapy. They found that people who believe that HIV is a man-made virus, that an HIV cure is withheld from the public, or that antiretroviral drugs are being tested on people by the government are significantly more likely not to follow the treatment plan (Bogart et al. 2010, p. 652).

Implications from believing in conspiracy theories are not limited to health-related choices. Swami (2012) carried out a study in which he investigated whether belief in Jewish conspiracy theories correlates with anti-Isreal attitudes. He was able to show not only that this is the case, but also that belief in Jewish conspiracy theories is associated with "higher racism, greater social dominance orientation, greater right-wing authoritarianism, stronger belief in general conspiracy theories" (Swami 2012, p. 6). Although Swami (2012) points out that these anti-Semitic statements may actually be more likely directed against the Chinese and may only be a symptom of the repressive political cli-

mate in Malaysia (Swami 2012, p. 7), it nevertheless shows that conspiracy theories could promote discrimination against minorities. Another study by Jolley & Douglas (2013) examined the influence of conspiracy theories about the government and climate change. They were able to show that belief in governmental conspiracy theories "reduced intentions to engage in politics" and that belief in climate change conspiracy theories "lowered intentions to reduce ones carbon footprint" (Jolley & Douglas 2013, p. 48).

These findings indicate the importance of research in the field of conspiracy theories, but also have limitations. A major shortcoming of the results of most studies is that they are merely "correlational" (Douglas et al. 2019, p. 19) , making it impossible to say with confidence whether Jewish conspiracy theories cause anti-Israeli attitudes or whether these attitudes cause belief in related conspiracy theories. After briefly explaining the significance of this thesis, the next section focuses on the dissemination of conspiracy theories and information on conspiracy theories.

4.2.2 How do conspiracy theories spread?

As argued in the first section of this thesis, many conspiracy theories are based on misinformation. It is therefore important to investigate not only how statements about one's own beliefs in conspiracy theories spread, but also how misinformation supporting conspiracy theories spreads. To investigate this, researchers analyze how information is disseminated in a social network, how it is received and adopted. First, a few common models of information diffusion will be presented, especially in the context of social media.

In the sense of a disease or an infodemic, as the WHO says, one would probably assume that information spreads similarly "through person-to-person contacts", but this is not the most commonly observed case when it comes to 'viral' diffusion (Tucker et al. 2018, p. 45). With regard to the diffusion of various items such as news, videos, images and petitions on Twitter, Goel et al. (2015) found that the diffusion was mostly characterized by "structural diversity" (Goel et al. 2015, p. 191). In this context, structural diversity means that diffusion could be observed not only through many individual interpersonal connections, but also through central broadcasters that have millions of followers and usually reach a large audience. In fact, Goel et al. (2015) found for the very largest diffusion events that they are "dominated by broadcasts" (Goel et al. 2015, p. 187) rather than 'virality'.

But can these general findings also be applied to conspiracy theories and misinfor-

mation? In the case of misinformation and conspiracy theories, many researchers turn to the concept of information cascades, which describes the phenomenon when people make decisions based on the opinions of others, ignoring the knowledge they may have themselves. In the case of misinformation, the following scenario would be imaginable. Person A reads a tweet about the dangers of vaccines and how doctors are paid by pharmaceutical companies to keep potential risks quiet. Person A believes that the content of the tweet is true and retweets it. Another person B sees the tweet from A and retweets it as well. Person C is not quite sure if vaccines are harmful or not, but because of his two friends who seem to think that vaccines are bad, he decides to follow them in his own judgment. This effect multiplies as the size of the cascade increases, because every time a person gives credence to the previous speaker, the information cascade continues (see Sunstein & Vermeule 2009, p. 213f). A study by Del Vicario et al. (2016) examined information cascades of conspiracy theories and science news. Two major findings emerged from this study. The first finding is that, despite the fact that in both cases most of the information diffuses quickly and peaks after 1-2 hours and 20 hours, if you look at the size of the information cascade, conspiracy theories show a positive correlation between lifetime and size, while scientific news are assimilated faster and no significant correlation is apparent (Del Vicario et al. 2016, p. 3). The second finding is that "social homogeneity is the primary driver of content diffusion, and one frequent result is the formation of homogeneous, polarized cluster" (Del Vicario et al. 2016, p. 5). The authors found that information often flows between friendly users who are similar in some aspects, which leads them to conclude that most users select information "according to a specific narrative" (Del Vicario et al. 2016, p. 4). This finding is consistent with previous research that suggests that people believe in conspiracy theories, in part because they fit into their own belief systems.

Another question is whether users tend to focus on one conspiracy theory or whether they engage in a variety of topics online. When looking at various conspiracy theories on the Italian Facebook, Bessi, Zollo, Vicario, Scala, Caldarelli & Quattrociocchi (2015) found that four main topics emerge: environment, diet, health and geopolitics. Social media users engaged with all four topics, jumping "independently from one topic to another" (Bessi, Zollo, Vicario, Scala, Caldarelli & Quattrociocchi 2015, p. 3). They also found a positive correlation between a user's activity and their mobility among the four different topics (Bessi, Zollo, Vicario, Scala, Caldarelli & Quattrociocchi 2015, p. 8). In fact, of the 68.050 users who liked at least 4 posts, most users engaged in 2 topics, followed by 3 and 4 topics, with the fewest users engaging in only 1 topic

(Bessi, Zollo, Vicario, Scala, Caldarelli & Quattrociocchi 2015, p. 9). These findings suggest that the hypothesis that general conspiracy predispositions correlate with the believe in multiple conspiracy theories may be true. In another study, Smith & Graham (2017) noted that a wide range of conspiracy theories are being discussed in anti-vaccination communities on Facebook, not only in relation to vaccination, but also in relation to the deliberate spread of the Zika virus and chemtrails (Smith & Graham 2017, p. 1325). A study by Mitra et al. (2016) comes to similar conclusions and shows that anti-vaccine advocates also post about government conspiracies on Twitter, linking anti-vaccine conspiracy theories with government conspiracy theories (Mitra et al. 2016, p. 275).

The process of liking and sharing may also play a central role in the diffusion of conspiracy theories online. Bessi, Coletto, Davidescu, Scala, Caldarelli & Quattrociocchi (2015) found that conspiracy news on Facebook received significantly more likes and shares than scientific news. Given the findings of Rudat & Buder (2015) that tweets with a high (perceived) informational value are more likely to be retweeted (Rudat & Buder 2015, p. 82) , this could be further evidence that some people believe and spread conspiracy theories because of social motives (see Douglas et al. 2019). Another important factor to consider is that tweets that receive many likes and shares could be perceived as more credible (see Tucker et al. 2018, p. 47). Considering that users in conspiracy communities show a high degree of interaction (see Bessi, Coletto, Davidescu, Scala, Caldarelli & Quattrociocchi 2015, p. 6f) - liking, tweeting, retweeting and sharing - it seems likely that the information disseminated through these communities appears to be more credible than content that receives less attention (e.g. likes, shares, etc.). This could also indicate why the size of the information cascades in conspiracy communities correlates with lifetime. The longer information circulates, the longer users have time to like and share the information. This could further enhance the credibility of the content, attract new users and thus continue the information cascade.

5 Theoretical framework

5.1 Network theory

As can be seen from the research carried out so far, the study and analysis of networks and their underlying structures is very important in the investigation of conspiracy theo-

ries and, in particular, the spread of conspiracy theories online. Since this thesis focuses on the study of social networks, some key concepts of network theory will be briefly explained in the following. Furthermore, this section will also define the basic terms used in the analysis part of this thesis.

5.1.1 Network structure, transitivity and homophily

Generally speaking, a network consists of a configuration of relationships between a certain set of objects. In network theory, objects are called nodes and their relationship to each other is described as an edge. In the context of social networks, the nodes typically represent an active actor such as a person or an institution. Edges represent a wide range of relationships, such as friendships, interactions, information flows and many other (see Borgatti et al. 2018, p. 4ff). The fundamental 'molecules', as Kadushin (2012) puts it, which make up all networks, are dyads and triads. Dyads consist of two interconnected nodes, and considering the type of relationship, it can be either a directed, a symmetrical or an undirected relationship. For example, if one Twitter user A follows another user B it is a directed relationship, but if the other users B also follows A, it is a symmetrical relationship. Undirected relationships often occur when there is insufficient data or when the direction of a relationship is not relevant to the research question. If a third node is added to the dyad it becomes a triad which "vastly increases the complexity of relationships" (Kadushin 2012, p. 23). Considering the 16 possible states in which these nodes could be positioned relative to each other, triads are the elementary building blocks of any imaginable network (see Kadushin 2012, p. 24). But how do these constellations come about? There are a few principles that try to explain why some people tend to develop connections and others do not. In this case, the concept of transitivity and of homophily will be discussed next. The concept of transitivity is derived from the balance theory first presented by Heider (1979). Put simply, it says that if person A has a strong connection to person B and B has a strong connection to person C, it is very likely that A will have a strong connection to C. More generally speaking, the proverbs "a friend of my friend is a friend of a mine" and "an enemy of my friend is an enemy of mine" correspond to the concept of transitivity (see Kadushin 2012, p. 23). The concept of homophily, on the other hand, suggests that people who are similar tend to be connected with each other. This applies to a wide range of characteristics and many different types of relationships (see McPherson et al. 2001). The 'similarity' refers to two different dimensions of characteristics. On the one hand, status-homophily, which includes socio-demographic characteristics, and on

the other hand, value-homophily, such as religious affiliation (see Lazarsfeld & Merton 1954). It is important to keep in mind that homophily is usually a process. Similar people with the same attitudes tend to come together, influence each other and become even more similar, causing a feedback loop (see Kadushin 2012, p. 19f).

But how do these principles affect the structure of a network? If one considers both principles and looks at a group of close friends, one could assume that their friendship network is very dense. Network density essentially describes how many edges are possible between a certain number of nodes and relates them to the actual number of edges. If you put the 10 possible edges of a group of 5 friends in relation to the 5 edges that are actually present, you get a network density of 50%. Most networks have a much lower density, especially when networks are not small groups of friends but larger constellations like those between employees in a company. If networks are very dense, they most likely represent a cohesive community. In this case, high density allows for easy and quick transmission of ideas, great social support and trust in each other (Kadushin 2012, p. 29). But people have a limited number of stable, strong connections that they can have with other people at the same time, so there must be other ways in which information can spread across multiple dense networks. To further explore this question, it is first necessary to explain the difference between strong and weak connections.

5.1.2 Strong and weak ties

The distinction between strong and weak connections, or as they are called from now on, strong and weak ties goes back to a popular article by Granovetter (1973).

The strength of a tie can be defined as a "combination of the amount of time, the emotional intensity, the intimacy (mutual confiding), and the reciprocal services which characterize the tie" (Granovetter 1973, p. 1361). With regard to the concept of transitivity, Granovetter (1973) argues that in a triad of two strong ties, the third tie must be either a weak or a strong tie - in no case is there no relationship at all (Granovetter 1973, p. 1363). In order to explain the significance of this argument, the concept of a bridge in a social network must first be explained. A bridge describes the connection between two nodes if the contacts of these nodes would be otherwise not be connected. As a consequence, bridges have the ability to connect separate network clusters, which can increase the flow of information and ideas. From the premise that there is no triad in which two strong ties exist and none else, Granovetter (1973) concludes that "no strong tie is a bridge" (Granovetter 1973, p. 1364), which in turn means that only weak

ties can be bridges. This highlights the importance of weak ties, especially for the flow of information in large networks with low density. Among the limitations of analyzing weak ties are that their definition is not as clear as one would wish, and that in networks many weak ties do not function as bridges at all (Kadushin 2012, p. 31).

5.1.3 The network structure of conspiracy theory communities

Now that the basic concepts for discussing social networks are established, how can networks in which conspiracy theories circulate be described from a network theory perspective? Given the principle of homophily and previous research that suggests that people who believe in conspiracy theories are similar in that they share either the same ideological or conspiratorial dispositions, these networks should be relatively dense and clustered. Indeed, Del Vicario et al. (2016) observe that misinformation diffuses through very dense networks, which limits the influence of crucial hubs (Del Vicario et al. 2016, p. 3) and that these networks are strongly characterized by homogeneous clusters (Del Vicario et al. 2016, p. 5). As a result, these networks are less dependent on weak ties and central actors than other networks. In a study by Smith & Graham (2017), the authors examined six anti-vaccination pages on Facebook where conspiracy theory content is disseminated. They find that the network of users behind these pages is very large, but the users themselves may be described rather "as 'transient' visitors" (Smith & Graham 2017, p. 1318), as the majority of users have only liked or commented on a post once or twice in 3 years (Smith & Graham 2017, p. 1316). On the other hand, however, they found that the overall network consists of many, strongly interconnected clusters, which themselves are only loosely connected, which is reflected in a far above average local clustering coefficient (Smith & Graham 2017, p. 1318f). They also found that users "are moderately active across several anti-vaccination Facebook pages" (Smith & Graham 2017, p. 1323), which is consistent with results from previous studies (see Bessi, Zollo, Vicario, Scala, Caldarelli & Quattrociocchi 2015). The low density values (see Smith & Graham 2017, p. 1318) indicate that the observed network may be more dependent on weak ties to achieve high degrees of diffusion.

Two studies by Shin et al. (2016) and Wood (2018) look at networks in which misinformation is disseminated from a different perspective. Botch studies compare propagating and debunking networks, in the case of the study by Wood (2018) explicitly conspiracy theories concerning the Zika virus and in the case of the study by Shin et al. (2016), the spreading of (false) political rumors during the U.S. election in 2012. However, the methodology and results vary. Shin et al. (2016) found that the

network of rumor believers and rumor spreaders forms two separate communities that run exactly along partisan lines (Shin et al. 2016, p. 1222f). The density of the anti-Obama rumor community was much higher compared to the anti-Romney rumor and debunking communities (Shin et al. 2016, p. 1224). The authors conclude from these findings that "the circulation of rumors occurs within 'echo chambers' defined by political homophily" (Shin et al. 2016, p. 1226), which is again consistent with previous research. Wood (2018) focused less on network density and more on centralization. This basically means investigating whether the diffusion processes in a network are more or less dependent on a few, very influential actors who, due to their favorable positioning in the network, may be able to restrict or promote the flow of information. Wood (2018) found that while the debunking network is more centralized overall than the propagator network, the propagator network "was more heavily centralized around a few highly influential accounts" (Wood 2018, p. 488). More interestingly, "more successful conspiracy theories were disseminated widely by some highly influential user" (Wood 2018, p. 488), further emphasizing the importance of these influential users.

Wood (2018) also suggests that future research should examine "the role of the influential propagators that shape the dynamics of their network" (Wood 2018, p. 488). But how does one measure the (potential) influence that an actor in a network has? In this thesis, the classical concept of opinion leadership is used to identify key actors in conspiracy networks. Opinion leadership is made measurable by applying the network theory concept of 'brokerage' and 'closure'. In the following, these two concepts will be explained in more detail.

5.2 Opinion leadership and the two-step flow of communication

The theory of the two-step flow of communication is on of the earliest communication theories, which was first popularized by the study "The people's choice" by Lazarsfeld et al. (1968)[3]. Later, this model was tested in the study "Personal Influence" by Katz & Lazarsfeld (2006)[4] and further developed on the basis of the results.

In the first study, Lazarsfeld et al. (1968) examined the decision-making process of voters during a presidential campaign in 1940, with particular interest in those who changed their mind during the campaign. Among the participants in the study, they found a group of people who were especially interested in the election campaign and who also articulated their thoughts most clearly. These persons were referred to as

[3]Originally published in 1944 by Duell, Sloan and Pearce
[4]Originally published in 1955 by The Free Press.

"opinion leaders". The authors identified them by asking whether they tried to convince someone of their own political opinion and whether someone asked them for their opinion. The opinion leaders, who made up 21% of the participants, all showed higher levels of interest in politics and a higher exposure to the media (Lazarsfeld et al. 1968, p. 49ff). They later conceptualized their results in the model of the two-step flow of communication. The model implements the crucial role of opinion leaders in the outdated stimulus-response model and states that "ideas often flow from radio and print to the opinion leaders and from them to the less active sections of the population" (Lazarsfeld et al. 1968, p. 151).

This model and the concept of opinion leaders were further explored in the study by Katz & Lazarsfeld (2006). In this study the authors applied the concept of opinion leadership to many different 'fields of interest', such as fashion and movies, not just politics. Again, they found that opinion leaders generally have a higher level of media use than non-opinion leaders (Katz & Lazarsfeld 2006, p. 312), although the form of media varies and is usually determined by the importance of the media form for the field of interest (Katz & Lazarsfeld 2006, p. 316). But opinion leaders do not communicate media content one-to-one to their peers. Opinion leaders are likely to communicate only selected content related to their personal opinions, and regardless of whether they do so intentionally or unintentionally, they are unlikely to provide a neutral picture. Katz & Lazarsfeld (2006) link this issue to the "gatekeeping" approach - another common concept in communication science. A "gatekeeper" is defined by having strategic control over a flow of any kind. In this context, a gatekeeper has a favourable position in a network and can therefore exercise control over the flow of information and ideas. This concept is directly related to the argument of weak ties and will be discussed further in the section on structural holes. Katz & Lazarsfeld (2006) could not find out exactly whether the gatekeeper function of a person causes that person to become an opinion leader as well, or whether it is the other way around, but in most cases the role of an opinion leader was coupled with the role of the gatekeeper (Katz & Lazarsfeld 2006, p. 123f). The question of how a person's positioning in a network affects his or her opinion leadership was further examined in an article by Katz (1957), in which he summarized the results of earlier studies regarding the two-step flow. Katz (1957) notes that opinion leaders must not only act as experts in their field of interest, but must also be accessible. This suggests that opinion leadership also depends on the "central location in the web of interpersonal contacts" (Katz 1957, p. 74). This insight is important because it indicates that opinion leaders can theoret-

ically be identified not only through surveys and self-identification, but also through the analysis of social networks. Looking at the opinion leaders and their 'followers', Katz (1957) found that they are "very much alike" and move in the same social circles (Katz 1957, p. 77). This finding corresponds to the principle of homophily and shows that the principle also applies to opinion leadership. Finally, while acknowledging that opinion leaders are more exposed to the media than others, he notes that "most opinion leaders are primarily affected not by the communication media but by still other people" (Katz 1957, p. 77). This last finding, although it was not discussed further at that time, suggests that the two-step flow of communication could indeed be a multi-step flow of communication. Based on this idea, the theory was later taken up again and modified by some researchers. Looking back at the concept of information cascades, it can be seen that both concepts have some similarities. In fact, they both describe that information is diffused in several steps or stages, although the concept of information cascades does not refer to opinion leadership.

Now that the importance of opinion leadership in networks has been clarified, the question arises of how to measure opinion leadership in order to identify key nodes in a network. One approach to do this is through the network mechanisms Ronald Burt proposed, which he calls brokerage and closure.

5.3 Structural holes and opinion leadership as 'Brokerage' and 'Closure'

This theory has its origins mainly in the theory of social capital popularized by Bourdieu among others. Burt (1999) linked social capital research with diffusion research, especially with the concept of opinion leadership. This argumentation will be examined in more detail after a brief summary of Burt's work on structural holes and the concept of brokerage and closure.

Burt (1992) defines a structural hole as a connection between two non-redundant actors (Burt 1992, p. 18). Redundant contacts are those that lead to the same information and ultimately cannot offer a person any additional informative value. According to Burt (1992), indicators for redundancy are cohesion and structural equivalence. Two contacts are considered redundant according to the criterion of cohesion if both have a strong relationship to each other. This is because you have access to both people who have a strong relationship with each other, such as a married couple, even if you are only connected to one of them. Structural equivalence refers to the contacts that in turn

have the same contacts, so that the information gained from these contacts is redundant, even if the contacts themselves are not connected (Burt 1992, p. 18f). From this Burt (1992) concludes that the occurrence of redundancy is most likely when there is a strong bond between structurally equivalent individuals, and most unlikely when they are "total strangers in distant groups" (Burt 1992, p. 20). Besides the potential gain in information by bridging a structural gap, actors can gain an advantage by exercising control. Burt (1992) calls this the "Tertius Gaudens", which describes a constellation of three actors, in which one actor has the opportunity to play the other two actors off against each other due to his favorable position (Burt 1992, p. 30-33). The previously mentioned weak tie argument by Granovetter (1973) is closely related to structural holes. They both seem to describe similar phenomena (Burt 1992, p. 27). But Burt (1992) argues that structural holes capture the essence of the phenomenon itself, whereas the 'weakness' of a tie occurs only as a correlate with a structural hole, not as the cause (Burt 1992, p. 27). In fact, most weak ties do not even bridge structural holes, only those that connect non-redundant actors in a network (Burt 1992, p. 30).

Burt (2005) developed this concept into a sophisticated theory in his book "Brokerage and Closure", in which he argues that social capital[5] is accumulated in two different ways. One of which he describes as "brokerage", which explicitly refers to the concept of structural holes. Burt (2005) argues that structural holes have an inherent potential value that is realized by bridging these holes, thereby increasing access to a more diverse range of information sources (Burt 2005, p. 18). While brokerage describes the bridging of structural holes, the people who build these bridges are called brokers. By managing "the flow of information between people" (Burt 2005, p. 18), brokers increase the social capital of the entire network, because not only they, but also the people close to them benefit from the increased flow of information (Burt 2005, p. 59).

In contrast to brokerage, Burt (2005) proposes a second way of accumulating social capital, which he calls "closure". Simply put, closure describes the degree of embeddedness in a strong web of relationships. Although bridging structural holes opens up new opportunities, it is often risky to trust new contacts that have been established in this way (Burt 2005, p. 95f). On the other hand, actors who are embedded in a close network of relationships can trust the information circulating in their personal network much more easily. This is because in such networks inconsistent behavior is easy to detect and therefore easy to punish. Burt (2005) describes this as the reputation mech-

[5] Burt (2005) defines social capital as an advantage resulting from a favorable position in a network (Burt 2005, p. 4).

anism that increases social control and thus facilitates trust (Burt 2005, p. 109). In this case, redundancy is considered positive, as it further increases the reliability of the information (Burt 2005, p. 162). But is this information reliable and trustworthy in the sense that it is true? Burt (2005) argues that the information circulating in these dense networks is in fact highly filtered and structured, adapted to the expectations and requirements of the group. This is what he calls the echo hypothesis, which states "that closed networks do not enhance information flow so much as they reinforce predispositions." (Burt 2005, p. 168). This could indicate that the self-sealing properties of conspiracy theories and the echo chambers observed by research are indeed a result of closure.

Burt (1999) connects brokerage with the concept of opinion leadership discussed earlier. He argues that opinion leaders within a group are less to be understood as leaders than as brokers between groups (Burt 1999, p. 51). Referring to the concepts of cohesion and structural equivalence mentioned earlier, Burt (1999) says that information within groups is distributed through equivalence rather than cohesion, which is more associated with opinion leaders (Burt 1999, p. 47). But this argument captures opinion leadership in a one-dimensional way and may therefore not be sufficient. As Katz (1957) argued, opinion leadership also depends on the central position of an actor in the network. It might therefore be important to understand opinion leaders also as accessible and visible.

6 Research question

In this section, empirical research and theory will be summarized in a concluding argument, which ultimately leads to the research question of this thesis.

Previous research gives reason to expect that the influence of opinion leadership on the way information is disseminated in networks of conspiracy theory is low. Dense networks indicate a high degree of homophily and closure, which may be directly related to the self-sealing properties of conspiracy theories (see Sunstein & Vermeule 2009) and the exceptionally high resistance to corrective information. The observed echo chambers suggest that crucial nodes, such as opinion leaders, should not play a prominent role in the dissemination of information (see Del Vicario et al. 2016). Nevertheless, we see that the activity and mobility between the various conspiracy theories is high (see Bessi, Zollo, Vicario, Scala, Caldarelli & Quattrociocchi 2015), indicating that some opinion brokers mediate between the networks. Other studies also point to

the importance of less central actors (see Wood 2018). So the question arises whether the same network mechanisms play a role or whether opinion brokers gain influence when several conspiracy theories are considered and not just one specific theory. Much of the research so far has focused on only one conspiracy theory at a time and has explored, if at all, only overlaps in content with other conspiracy theories (see Smith & Graham 2017). In this thesis, several different conspiracy theories are considered. If one takes into account the research on predispositions that influence the belief in conspiracy theories, one might also expect people to believe in a variety of conspiracy theories, regardless of whether the theories support or contradict each other (see Wood et al. 2012). The argument presented by Uscinski et al. (2016) also suggests that networks of ideological conspiracy theories may be more disconnected from other non-ideological conspiracy theories, which in turn opens up more opportunities for opinion brokers.

This thesis intents to provide an answer to the role and importance of opinion leaders and brokers in networks of conspiracy theories. More specifically, it attempts to understand the "function" of opinion leaders and brokers in conspiracy networks by looking at the mobility of actors across a variety of different conspiracy theories. The research question of this paper is as follows:

> RQ1: Do opinion leaders act across different conspiracy networks or do they function as "experts" for only one conspiracy network?

7 Methodology

To answer the research question presented, this thesis uses a methodological approach that focuses on the methods of social network analysis. To conduct the social network analysis, Twitter data of four conspiracy theories were collected over a period of 6 weeks. In this section the process of data collection will be explained first and then the methodological approach of this thesis will be presented in more detail. Both data collection and analysis were performed with R. To calculate the network metrics the package 'igraph' was used.

7.1 Data collection

The first question regarding data collection that needs to be answered is what conspiracy theories should be collected. The answer to this question is guided more by

practical than theoretical reasons. The data traces of the conspiracy theories must be able to be properly captured by keywords and, at best, must not be diluted by sarcasm, trolls and, above all, a debunking community using the same keywords. Furthermore, conspiracy theories should also be discussed enough on Twitter so that the data set is large enough for analysis. On the other hand, the conspiracy theories chosen must also be discussed broadly enough in the general public so that the results are not completely confined to the Twitter sphere. Four conspiracy theories were selected on the basis of these criteria. Specifically, they are the anti-vaccine in the following called antivax conspiracy, the chemtrails conspiracy, the deepstate conspiracy, and the flatearth conspiracy. A brief summary of these theories reads as follows[6]: Supporters of the chemtrails conspiracy claim that under the guise of contrails, chemicals are sprayed into the atmosphere, which in turn are supposed to manipulate a variety of things, especially the weather. The legitimate science behind weather control, known as geoengineering, is struggling more and more for its terminology as the conspiracy community adapts its terms (see Tingley & Wagner 2017). Supporters of the deepstate conspiracy claim that there is a second government within the U.S. government, a hidden state consisting of bureaucrats and intelligence officials who act independently of elected officials and therefore always have control. Supporters of the flatearth conspiracy claim that the earth is flat, and argue for all the implications this would have, from fake moon landings to a complete rejection of physics and empirical science. Support for these conspiracy theories has been tested in several studies in different countries[7]. Beyond the practical reasons, these theories also represent a reasonably wide range of conspiracy categories. As Bessi, Zollo, Vicario, Scala, Caldarelli & Quattrociocchi (2015) show, there are essentially four conspiracy narratives, consisting of health, geopolitics, environment and diet. The antivax conspiracy represents a health narrative, the chemtrails conspiracy a mixture of health and environmental narratives, the deepstate conspiracy a geopolitical narrative, and the flatearth conspiracy an environmental narrative. The analysis does not include any theory that represents a diet-related narrative, but out of all categories, the diet-related narrative seems to be the least attractive topic. (Bessi, Zollo, Vicario, Scala, Caldarelli & Quattrociocchi 2015, p. 7).

In order to carry out the keyword-based data collection of the four conspiracy theories, random samples were first collected from November 20th 2019 to November 30th 2019. The initial keyword search used only the respective name of the conspir-

[6]The anti-vaccine conspiracy was already presented in section 4.2.1.
[7]See Oliver & Wood (2014), Drochon (2018), YouGov (2019).

acy theory (e.g., the deepstate conspiracy was collected with the keyword 'deepstate'). Unfortunately, the anti-vaccination community did not use a self-descriptive term. The term 'antivax' used by media and critics is not accepted in the community and would probably distort the data set. In this case a sample was collected using the keywords 'vaccination' and 'vaccines'. From these samples, the 100 most commonly used hashtags were extracted. From this list, keywords used exclusively in the respective conspiracy were selected for the final data collection. For example, the keyword 'spaceisfake' was selected for the flatearth conspiracy, but not the keyword 'wakeup'. In the context of the flatearth conspiracy, both appear to be conspiratorial, but the latter actually appeared in all lists, is therefore by no means exclusive and could possibly be used in a completely unconspiratorial manner.

This process resulted in a total of 18 keywords. These keywords were then used in a keyword-based search for tweets with the R package "rtweet". The code was executed every fifth day from December 1st to February 1st using Twitters Rest API. Due to a technical problem, data was missing from the chemtrails data set from January 1st to January 9th, which ultimately resulted in the exclusion of all data during this period. This should not affect the results, as no analysis of effects related to a time variable is planned. After all data was collected, the data sets were merged and tweets collected multiple times were excluded. Due to the way rtweet works, tweets were also collected from users whose username contained a keyword, even though their tweet did not contain a keyword. The same happened when these users were mentioned in a tweet. These tweets were also excluded. In addition, all non-retweets that were shared from other platforms using the share feature were excluded[8]. During the six-week period a total of about half a million tweets was collected (see Table 1).

	Number of unique tweets	Number of retweets
Antivax	9606	59597
Chemtrails	54167	78995
Deepstate	60904	210865
Flatearth	16054	22194
Total[*]	140471	370693

[*]Numbers are lower because some tweets contain multiple keywords therefore appearing in multiple datasets.

Table 1: Conspiracy theory Twitter sample size

[8]Some platforms, such as YouTube, add the phrase "via @YouTube" at the end of a shared tweet by default. This mention would be included in the analysis, although it could be argued that the meaning of such a mention is different from a regular mention.

7.2 Methodological approach

To answer the proposed research question, this paper focuses on three aspects of conspiracy networks on Twitter.

First, it is important to determine how many people on Twitter interact with and produce conspiracy theory content. Previous studies suggest that users are not only focused on one conspiracy theory, but often interact with other theories as well. In such cases it is interesting to analyze which conspiracy theories have the largest number of overlapping users and to see if this is accompanied by narrative similarities. In addition, the general mobility of users will be analyzed to see if there are differences between the conspiracy theories. These results could provide a first indication of whether opinion leaders follow these mobility patterns. Again, previous studies suggest that there may be differences between conspiracy theories, depending on whether they correspond more to conspiratorial or ideological predispositions. In the case of the four conspiracy theories analyzed in this paper, the deepstate conspiracy theory stands out because it has a clear political-ideological reference in contrast to the other three. To measure the general mobility of each user, the total amount of tweets is counted across the four respective conspiracy theories and summarized using the Gini coefficient. The Gini coefficient is usually used as a measure of inequality, often to represent the income distribution of a population in a single number. In this context, the Gini coefficient represents the degree of equality (or inequality) with which a user tweets about the four different conspiracy theories. Because of the way the coefficient is calculated, it takes into account how many times a user has tweeted overall about a conspiracy. Users who have tweeted very often about one conspiracy theory and only once about another will not be much different in their mobility from users who have tweeted exclusively about one conspiracy theory. To be consistent with the interpretation of the mobility variables, the resulting Gini coefficient is inverted so that a high coefficient represents high mobility.

The second aspect is the extent to which the collected tweets form networks that represent a community structure. From the collected data two types of networks were created. Firstly @-mentions networks, which were created by extracting the username of a mentioned user from a tweet together with the username of the author. Given the main objective of this work, to analyze opinion leadership in these networks, the decision was made to exclude all users who were mentioned but who did not tweet at least once about any conspiracy theory. For example, if all users were taken into account, a news agency or a politician could be classified as an opinion leader even though they

have never disseminated misinformation or conspiracy theories. The second type of network are retweet networks, which were created by extracting the username of the original tweet and the username of the user who retweeted the tweet. A total of 10 networks were generated this way. From each conspiracy theory data set, one @-mentions and one retweet network were generated. In addition, one global @-mentions and one global retweet network were created from the data of all conspiracy theories. Duplicates of tweets that were present in multiple data sets were excluded for the global networks. To determine whether these networks follow a community structure, the main component of each network (see Table **??**) was selected and the modularity Q was calculated using the fast and greedy community detection method. This will be the basis for classifying the significance of the role of opinion leaders and opinion brokers in the conspiracy theory networks. A high modularity value represents a strong community structure with clearly defined groups, a low value means that the structure is hardly different from a randomized network with the same number of nodes and edges.

	Nodes	Edges
Global @-mentions network	15 405	71 899
Main component	11 842	68 766
Global retweet network	123 364	370 539
Main component	114 175	363 330

Table 2: Main component of the global @-mentions and global retweet network

The third and most important aspect is opinion leadership itself and the extent to which opinion leadership is evident in each of the networks analyzed. The main objective of this study is to determine whether opinion leaders are experts in only one conspiracy theory or whether their role goes beyond that. As argued in the theoretical framework, opinion leaders are defined as opinion brokers, which in turn are related to the concept of brokerage proposed by Burt (2005). Brokerage is operationalized by the Network Constraint Index[9], also developed by Burt. The Network Constraint Index is a value calculated for each user and is high when a user has more redundant contacts and is therefore more constrained in his network position and his ability to bridge structural holes than users who have a high number of non-redundant contacts. To match

[9]With this decision, this methodological approach follows the methodology of other studies that have analyzed Burt's brokerage, especially the studies by Sajuria et al. (2015) and González-Bailón & Wang (2016)

the interpretation of brokerage, the calculated constraint values are inverted. However, since opinion leaders also depend on being visible and reachable in the networks, the visibility of users in the networks is also examined. The visibility variable is operationalized by in-degree centrality, a network metric introduced by Freeman (1979). In the case of the @-mentions network, a high in-degree value would indicate that a user was mentioned very often by other users, and in the case of the retweet network, a high value would indicate that a user was retweeted very often. Especially in the latter case, a high visibility could also be associated with a high influence, as each retweet expands the potential audience for conspiracy theory content.

The analysis of opinion leadership is divided into two sections. First, the local networks are examined for their brokerage value. To find out whether a user who is an opinion leader in one conspiracy network is also an opinion leader in another network, the brokerage values of users who are active in both networks are examined. If a positive correlation is found, this would indicate that users who are opinion leaders in one network also play a similar role in another network. The same is done with the visibility values of users in the respective networks. This would indicate whether users who are frequently mentioned in one network are also frequently mentioned in other networks. In the case of the retweet network, this will show whether users are frequently retweeted across different networks. However, in order to be frequently retweeted across different conspiracy theories, users need to tweet about multiple conspiracy theories in the first place. In addition to local correlations, it is also investigated whether users who act as opinion leaders for a conspiracy network are also opinion leaders or rather opinion brokers on a global level. The global network includes all conspiracy theories and therefore users who have a high degree of brokerage in these networks are able to bridge the structural holes between the individual conspiracy networks. At the global level, the analysis will address the relationship between local and global brokerage on the one hand, and whether the average brokerage values change with the introduction of other conspiracy networks on the other. The latter is done by comparing the local and global mean of the brokerage values of the individual conspiracy theories, which provides information not only about the direction in which the values change, but also about how large or small the difference between the local and global brokerage value is. To analyze the correlation between local and global brokerage values another network measure is introduced. Due to the way the network constraint index is calculated, the value of a user only changes if the user gets new contacts due to the change of perspective to the global level. This would strongly influence the correlation values. To measure opinion

leadership at the global level, the betweenness centrality metric is used. Betweenness centrality is another network metric that refers to the broker or gatekeeper position in a network, but it is calculated differently. In contrast to constraint, this metric focuses less on the redundancy of contacts and more on the position of the node in relation to all other nodes. A high betweenness centrality essentially describes that a user is very often part of a path that connects two nodes. Especially on a global level, this metric should be as appropriate for opinion leadership as the network constraint index.

In addition to the overlap of local opinion leadership and the comparison of opinion leadership at local and global level, the relationship between visibility, mobility and opinion leadership will be investigated. As Katz (1957) argues, it is also important for opinion leaders in their network position to be accessible. Visibility is operationalized in this respect in three dimensions: the number of mentions received, the number of retweets, and third, the number of followers. Especially the relationship between the number of followers and brokerage is interesting, since the number of followers only indirectly influences brokerage values. Correlations between mobility and opinion leadership also provide further insight into whether a user's mobility is related to opinion leadership. A comparison between the correlations between local brokerage values and mobility and global brokerage values and mobility can also indicate whether local opinion leaders tend to focus on one conspiracy theory or also tweet about other conspiracy theories. Again, the mobility variable operationalized by the Gini coefficient is used for this purpose.

8 Results

8.1 Tweeting about conspiracy theories

To get a first idea of how much attention conspiracy theories get on Twitter, for each conspiracy theory the number of users who tweeted about the conspiracy theory was counted. Most users tweeted about the chemtrails conspiracy theory ($n = 25833$), followed by deepstate ($n = 17352$), and the least tweeted about the flatearth ($n = 3837$) and antivax conspiracy theory ($n = 3021$). The users of each conspiracy theory were also broken down by their activity overall to determine the percentage of users who exclusively tweeted about one or more conspiracy theories (see Fig. 5). Overall, users mostly tweeted about only one conspiracy theory, with the antivax conspiracy theory having the most users relative to the total number of users who tweeted about two

or more conspiracy theories (19.4%) and the chemtrails conspiracy theory having the least (6.4%). Over a period of 6 weeks there were only 18 users who tweeted about all four conspiracy theories. This picture changes with regard to the retweet activity of the users. The percentage of users who retweet more than one conspiracy theory increases compared to the tweet activity in every conspiracy theory (see Fig. 6). Of the users who retweet tweets about the antivax conspiracy theory, almost 50% retweet other conspiracy theories as well. Furthermore, the number of retweets is generally higher compared to the number of tweets, regardless of the conspiracy theory. What is particularly noticeable is that the ratio of tweets and retweets is higher with the antivax and deepstate conspiracy theory ($\sim 1:4$) than with the flatearth and chemtrail conspiracy theory ($\sim 1:1.5$). Comparing the mobility of users according to the conspiracy theory they tweet about, a big difference can be seen between the deepstate conspiracy theory and the rest. Regardless of whether it is the tweet or retweet mobility, users who engage with the deepstate conspiracy theory are significantly less mobile than users who engage with other conspiracy theories. There are also significant differences in mobility between users of other conspiracy theories, but as shown in Figure 7, these differences are much less pronounced than the difference between deepstate users and users of other conspiracy theories.

8.2 Graph-level network analysis

The analysis of the networks on a graph level shows that most conspiracy theory networks are characterized by community structures, but some more so than others. These community structures give an indication of how freely information can circulate in these networks. A network that consists of several dense clusters opens up the possibility for opinion leaders to act as brokers, enabling but also controlling the exchange of information between the networks. Looking at the modularity Q in Table 3, a strong community structure can be seen especially in the global, chemtrails and deepstate @-mentions network and the chemtrails retweet network. Furthermore, in the case of the chemtrails retweet network, the number of communities that make up the overall network is extraordinarily high compared to the other networks. In contrast, the antivax and flatearth @-mentions networks and the antivax and deepstate retweet networks have relatively low modularity values. This could indicate that in Burt's terms the flow of information in these networks is characterized more by closure than by brokerage. These results are later taken into account in the interpretation of the results of the node-level analysis.

Conspiracy theory network	$N_{Communities}$	Q
Global	128	.75
Antivax	33	.48
Chemtrails	83	.75
Deepstate	57	.72
Flatearth	27	.40

(a) @-mentions networks

Conspiracy theory network	$N_{Communities}$	Q
Global	459	.60
Antivax	120	.53
Chemtrails	409	.75
Deepstate	137	.51
Flatearth	112	.63

(b) Retweet networks

Table 3: Community structure using the fast and greedy approach

Nevertheless, these results show that most networks provide brokerage opportunities, which in turn strengthen the role of opinion leaders. In the next section these actors will be examined in more detail.

8.3 Node-level network analysis

8.3.1 Local opinion leadership

As described in the methodological approach, this section will focus on the question of whether opinion leaders act not only in one but also in other conspiracy networks.

In total, only two significant correlations between brokerage in the local @-mentions networks became apparent. As can be seen in Table 4, the Pearson correlation coefficient shows a weak positive correlation in both cases $(0.1 < r < 0.2)$. The most significant correlation between chemtrails and deepstate also represents the largest group of users who tweeted about more than one conspiracy theory. However, it must be considered that users can act as opinion leaders even if they have not tweeted about both conspiracy theories during the survey period. They could still occupy a central network position in these networks. A closer look at Fig. 8a shows that many users have different levels of brokerage in one network and a brokerage value of 0 in the other network. These are most likely users who are active in one network but have only been mentioned once in the other network or only once mentioned a user in the other network, resulting in a very low brokerage value. Looking at users who have a brokerage value above 0 in both networks, it can be seen that relatively many data points are concentrated in the upper right quartile. If one looks at the local regression line, one can see that the correlation in this section is particularly strong. The other, slightly less significant correlation is between the chemtrails and the flatearth @-mentions network. In this case, the scatterplot differs only slightly, but the data points are less concentrated

in the upper right section and more scattered overall (see Fig. 8b).

@-mentions network brokerage	*M*	*SD*	1	2	3	4
Antivax	0.38	0.36				
Chemtrails	0.31	0.33	.00			
Deepstate	0.30	0.33	−.17	.17**		
Flatearth	0.38	0.35	.02	.15*	.00	

*$p < .05$, **$p < .01$

Table 4: Brokerage correlations for the @-mentions networks

Looking at the brokerage correlations between the local retweet networks, in contrast to the @-mentions network, all values are significant. As can be seen in Table 5, three correlation coefficients show a weak positive correlation ($0.1 < r < 0.2$). Brokerage values in the antivax and chemtrails network show the strongest correlation. Fig. 9a shows that many users have a high brokerage value in the chemtrails network, regardless of their brokerage value in the antivax network. There are very few users who have a brokerage value in the chemtrails network above 0 but below 0.5, resulting in many data points in the upper half. Fig. 9b, which shows the distribution of antivax and flatearth brokerage values, shows a similar pattern, but has significantly fewer data points, resulting in wider confidence intervals. The number of users who retweeted both antivax and flatearth tweets is also small compared to all other combinations of conspiracy theories. The third significant correlation between chemtrails and flatearth brokerage shows similar patterns to Fig. 8a, with a concentration of data points in the upper right quartile. The correlation between deepstate and flatearth brokerage is negative, as is the correlation between deepstate and antivax. However, these values are below 0.1 and therefore hardly count as weak correlations.

Retweet network brokerage	*M*	*SD*	1	2	3	4
Antivax	0.14	0.25				
Chemtrails	0.15	0.28	.18**			
Deepstate	0.28	0.34	−.04*	.09**		
Flatearth	0.20	0.30	.16**	.14**	−.07**	

*$p < .05$, **$p < .01$

Table 5: Brokerage correlations for the retweet networks

The analysis of the correlation between the visibility values of the local @-mention and

retweet values shows only three significant correlation coefficients and only one value above $r = 0.1$. This strongly suggests that users that are mentioned or retweeted in one network are generally not mentioned or retweeted equally often in other networks. In the case of retweet visibility, this could be a consequence of the overall low tweet mobility. Ultimately, users can only be retweeted in different conspiracy theory networks if they tweet about different conspiracies. Even if they tweet about several theories, but focus on one conspiracy theory, their in-degree centrality in different networks will most likely not overlap, since there is a strong positive correlation between the number of tweets and the in-degree centrality in the retweet networks of most conspiracy theories (see Table 11). The correlation coefficient between antivax and chemtrails retweet in-degree stands out because it is particularly high. However, a closer look at the scatter plot reveals that the strong correlation is due to the fact that there are mostly users who have very low in-degree centrality in both networks, and very few who have any value above 0 (see Fig. 1).

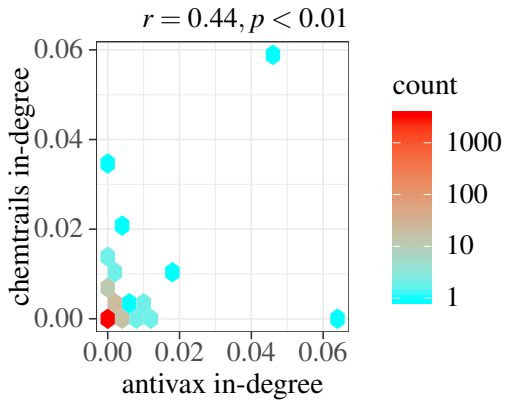


Figure 1: Scatter plot of antivax and chemtrails in-degree centrality in the local retweet network

In all cases the scatter plots revealed that most users have low degrees of brokerage in both networks with a high concentration of values in the bottom left. Considering the overall rather low correlation values, this suggests that opinion leaders in one conspiracy theory do not necessarily act as opinion leaders in another conspiracy theory, although the scatter plots show that there are a small number of users who have consistently high brokerage values in more than one conspiracy network.

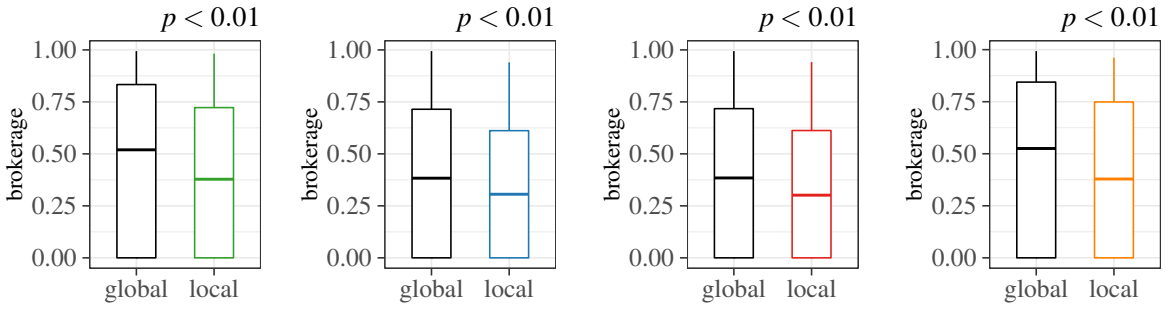
8.3.2 Global opinion leadership

As shown in the previous section, there is some overlap in opinion leadership between the local networks of conspiracy theory. Now the relationship between local and global opinion leadership will be further investigated. In contrast to local opinion leaders, global opinion leaders are rather between networks and bridge structural holes not (only) within conspiracy networks, but also between conspiracy networks. This section aims to answer whether global opinion leadership correlates with local opinion leadership or whether both roles are more or less separate. Furthermore, it will be analyzed whether the average brokerage of all users in the global network is higher than in the local network. The degree to which this effect is pronounced could give a better insight into the general embedding of all users in the global network. An increased value would indicate that users gain additional, non-redundant contacts from other conspiracy networks.

Fig. 10 shows that in all four local @-mentions networks the brokerage values of the users show at least a weak positive correlation with global brokerage. All measured correlations are very significant. The users in the chemtrails network show the highest correlation coefficient ($r = 0.22$), followed by the users in the flatearth and antivax networks ($r = 0.17, r = 0.13$) and finally deepstate users with the lowest correlation coefficient ($r = 0.09$). However, a closer look at the scatter plots shows that the values are quite scattered and follow the curve of the local regression line only to a small extent. In particular, Fig. 10c and 10b show that quite a lot of users active in the deepstate and chemtrails networks have high local brokerage values but low global brokerage values. In general, as shown in Fig. 2, average brokerage values increase in each conspiracy theory network. However, both antivax and flatearth users gain substantially more non-redundant contacts in the global network compared to deepstate and chemtrails users.

Looking at the local and global brokerage values in the retweet networks, the correlations are much weaker overall and less significant in the case of the flatearth users. The highest correlation coefficient between local and global brokerage is observed for antivax and chemtrail users ($r = 0.09$). Users in the deepstate and flatearth networks both have a correlation coefficient of less than 0.05, which hardly represents a very weak correlation. Looking at the Fig. 11, one can see that despite low correlation coefficients, chemtrails and deepstate users show a slightly positive trend, while it seems that the values of antivax and flatearth are more randomly scattered and less concentrated. The comparison between the average local and global brokerage values of the

Groups were compared using the paired Wilcoxon Rank Sum test

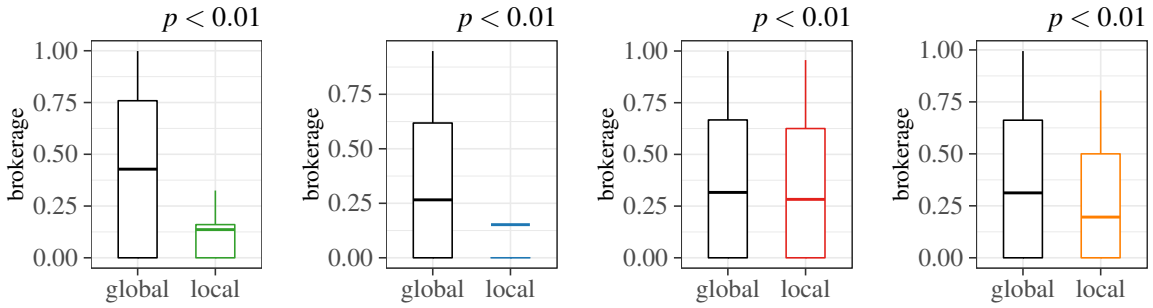


(a) Antivax **(b)** Chemtrails **(c)** Deepstate **(d)** Flatearth

Figure 2: @-mentions networks: global vs. local brokerage distributions

individual conspiracy networks shows a remarkable difference in the antivax retweet network (see Fig. 3). Antivax users seem to retweet more often tweets about other conspiracy theories and, if they are also tweeting about other conspiracy theories, they often get retweeted by users who are not active in the antivax network. In fact, tweeting mobility is highest among antivax users compared to all other users (see Fig. 7a). However, the average retweet mobility is at a relatively similar level for all users, except for deepstate users (see Fig. 7b). This is also reflected in the average brokerage values of the deepstate retweet network. As shown in Fig. 3c, deepstate users show only a marginal increase in brokerage values in the global network, indicating that deepstate users neither retweet other conspiracy theories nor are they frequently getting retweeted in other conspiracy networks.

Groups were compared using the paired Wilcoxon Rank Sum test



(a) Antivax **(b)** Chemtrails **(c)** Deepstate **(d)** Flatearth

Figure 3: Retweet networks: global vs. local brokerage distributions

In general, local and global brokerage appear to be positively correlated in almost all

cases. In the case of retweet networks, however, these correlations are quite weak. The correlation values are highest for the antivax and chemtrails networks. Looking at the general embedding of any conspiracy theory at the global level, it seems that antivax and flatearth users gain more brokerage opportunities by connecting with other conspiracy users. Deepstate and chemtrails users on average gain fewer non-redundant contacts from other conspiracy networks.

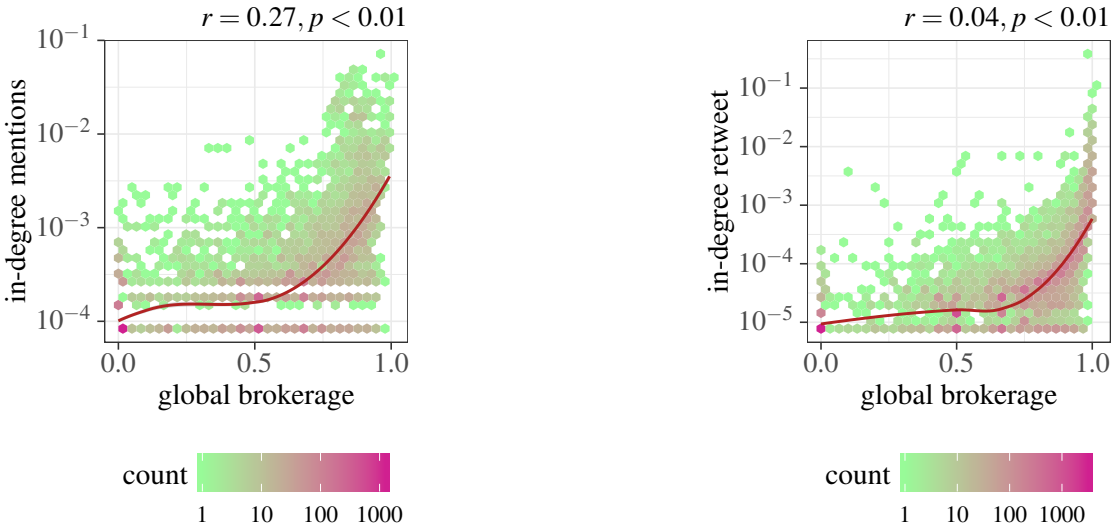
8.3.3 Opinion leadership and visibility

This section analyses the relationship between opinion leadership and visibility. Visibility is captured in two different dimensions. First, the relationship between the received @-mentions or retweets in the @-mentions or retweet networks and opinion leadership is examined. The second dimension of visibility is measured by the number of followers each user has.

Overall, there is a moderate positive correlation between the number of mentions received and the brokerage values. The correlation between global brokerage and global in-degree centrality in the @-mentions network is $r = 0.27$, which is highly significant. As can be seen in Table 10a, the correlation coefficients are quite similar for all networks, with the correlation being weakest in the deepstate network and strongest in the flatearth network. Fig. 4a shows that especially the higher brokerage values of the global network are associated with the number of mentions received. However, these high correlation coefficients could also be explained by the fact that brokerage values increase with the number of non-redundant contacts of a user. If a user is only mentioned by one other user, his brokerage value will definitely be low. If the user is mentioned by many other users, he could theoretically still be constrained if these users all belong to the same cluster, but with a higher number of mentions the chance of being mentioned by non-redundant contacts increases.

The correlation coefficients are considerably lower in the retweet network. The relationship between global brokerage and how often a user has been retweeted is weak at $r = 0.04$. Exceptions are users in the chemtrails and flatearth retweet networks, they show a slightly stronger correlation, but remain weak overall (see Table 10b). However, Fig. 4b shows that the overall value distribution is similar to the @-mentions networks. One reason for the different correlation values could be that the in-degree centrality at graph level of the retweet network is much higher than in the @-mentions network (0.39 vs. 0.07).

With regard to the relationship between the number of followers and network bro-



(a) @-mentions network

(b) Retweet network

Figure 4: Scatter plots of global brokerage and global in-degree centrality

kerage in both @-mentions and retweet networks, only weak positive correlations can be found. The correlation coefficients in the retweet networks seem to be somewhat lower in comparison (see Table 12). The deepstate @-mentions network is the only exception with a slightly higher value. Fig. 12 shows that there are actually many users who have a very low brokerage value, but a very varying number of followers. As the brokerage value increases, the number of followers also increases, although the values remain quite scattered.

8.3.4 Opinion leadership and mobility

Finally, the relationship between opinion leadership and mobility will be analyzed. In particular, the question whether tweeting about several different conspiracy theories correlates with opinion leadership in a network. In the case of retweet networks, retweet mobility will be investigated.

The results here are quite mixed. Looking at the correlation between @-mentions brokerage and tweet mobility, only two significant correlations are found (see Table 13a). Interestingly, the correlation between flatearth brokerage and tweet mobility is negative, while the correlation between global brokerage and tweet mobility is positive. This discrepancy continues and is even more pronounced in the relationship between brokerage in the retweet networks and retweet mobility. In this case all correlations are

very significant (see Table 13b). Users in the antivax, deepstate and flatearth networks show a negative correlation between brokerage and mobility. The latter two even show a moderate negative correlation. In contrast, the global network and, surprisingly, the chemtrails network show weak positive correlations.

This suggests that local opinion leaders tend to focus on one conspiracy theory in their tweeting and retweeting activities, and opinion leaders at the global level, who connect users from different conspiracy theories, tweet about several conspiracy theories. These results are not entirely unexpected, but nevertheless show that local and global opinion leadership are usually not united in one user, but that the roles are taken over by different users. The retweet chemtrails network stands out in this respect, as it shows a positive correlation between brokerage and mobility. This does not necessarily prove that in the chemtrails retweet network local opinion leaders also act as global opinion leaders, but it does show that users who have an influential position in the chemtrails network also engage in other conspiracy theories.

When it comes to the relationship between the number of mentions and retweets received and the tweet and retweet mobility, only very weak correlations can be found. Therefore, dealing with various conspiracy theories does not generally lead to greater visibility in the network. Retweeting tweets from different conspiracy theories even shows a weak negative correlation with the number of mentions a user has received ($r = -0.05, p < 0.01$). The correlation between tweet and retweet mobility is moderate($r = 0.35, p < 0.01$), which indicates that users who tweet about different conspiracy theories also retweet tweets about different conspiracy theories.

9 Discussion

The results presented above suggest an ambivalent answer to the proposed research question. Two different dimensions of opinion leadership have emerged through the analysis process. It seems that opinion leadership plays a role both on a local and global level. Most of the networks analyzed, both local and global, have a community structure, which in turn allows opinion leaders to bridge structural holes. Opinion leaders at the local level would therefore most closely correspond to the definition of experts that was used in the research question. Opinion leaders at the global level, on the other hand, have the opportunity to connect users of different conspiracy theories. These could therefore also bring users who are only interested in one conspiracy theory into contact with new conspiracy theories, which in turn could strengthen their conspiracy

beliefs. The results suggest that local and global opinion leadership are not necessarily united in one user. Especially in retweet networks, the relationship between local and global opinion leadership is very weak. However, the scatter plots show that there is probably a small "elite" of users who bridge structural holes in both local and global networks. This conclusion is also supported by the distribution of tweet and retweet activities. In particular, the tweet distribution shows that most users only tweet about one conspiracy theory (see Table 5 and 6), which limits their brokerage opportunities on a global level. In this context, the results by Bessi, Zollo, Vicario, Scala, Caldarelli & Quattrociocchi (2015), which indicate that the majority of users are dealing with more than one conspiracy theory, could not be replicated. The only exception are users who retweet antivax tweets. More than 50% of these users also retweet tweets about other conspiracy theories. It should be noted, however, that in this thesis a much smaller number of conspiracy theories were collected and analyzed than in the study by Bessi, Zollo, Vicario, Scala, Caldarelli & Quattrociocchi (2015). The analysis of the relationship between mobility and opinion leadership also supports the conclusion that the roles of local and global opinion leadership are taken over by different users. Especially in the local retweet networks, a negative correlation between mobility and opinion leadership can be found, suggesting that local opinion leaders are mainly focusing on one conspiracy theory. On the global level, however, the reverse pattern can be observed, which emphasizes the distinction between local and global opinion leadership.

No clear answer can be given to the question of whether local opinion leaders also act as local opinion leaders in other conspiracy theories, as the results here tend to be mixed. For example, there is no significant correlation between the @-mentions networks of the antivax and chemtrail conspiracy theory in terms of opinion leadership, but there is between the respective retweet networks (see Table 4 and 5). With regard to all conspiracy networks, a certain overlap of local opinion leadership between the various conspiracy theories can be observed, but no pattern can be identified that could be associated with similarities in content or other common factors. The only thing that stands out is that when looking at the retweet networks, all conspiracy theories showed at least a weak correlation of local brokerage values, except for the deepstate network. Here the correlation values were comparatively lower and in the case of the antivax and flatearth networks even negative values were measured. However, these coefficients were so low that they should rather be interpreted as no correlation at all, which is still a striking difference to the other conspiracy networks.

In general, among the various conspiracy theories, the deepstate conspiracy theory

differed the most from the other conspiracy theories. When looking at the mobility distribution, deepstate users showed the lowest values on average for both tweet and retweet mobility (see Fig. 7). Deepstate users also showed the smallest difference between average local and average global opinion leadership (see Fig. 2 and 3). Both findings suggest that deepstate users are little engaged with other conspiracy theories and are not very well connected in the global network of conspiracy theories as a whole. This is in line with the distinction proposed by Uscinski et al. (2016) between conspiratorial and ideological predispositions. Users with ideological predispositions are likely to be interested only in the deepstate conspiracy, since it is the only one of the four conspiracy theories associated with a clear political ideology. In fact, Trump used the deepstate narrative on several occasions, and his followers of the Qanon conspiracy movement often play with the same narrative.

In conclusion, conspiracy theories on Twitter receive varying degrees of attention. The antivax and flatearth conspiracies attract relatively few users, the chemtrails and deepstate conspiracies get in comparison much more attention on Twitter. Looking at the four conspiracy theories on a global level, it becomes clear that the global networks have a strong community structure and that only a few users act as opinion brokers between the various conspiracy theories. Of all users, antivax users on average have the highest global brokerage opportunities. On the local level, however, the flow of information seems to be less dependent on opinion brokers, depending on the conspiracy theory. Whether information diffusion in the @-mentions networks depends on opinion brokers or structural equivalence seems to be determined primarily by the number of users (see Table 6). This could be explained by the fact that more dense network clusters often form as the number of users increases. The deepstate retweet network falls out of this pattern. Of all retweet networks it has the most users, but the smallest modularity value. Opinion brokers will have a less important role in this network, which suggests that information diffusion is more likely to be through structural equivalence. Referring to Burt's echo hypothesis, this indicates that by retweeting each other, users in the deepstate network do not improve the flow of communication, but only reinforce each other's predisposition. This structural characteristic of the network, along with the distinction between conspiratorial and ideological predispositions, could be a further reason why users in the deepstate network tend to focus only on one conspiracy theory.

10 Limitations

As with any study, there are some limitations to be considered. First, the general restrictions of Twitter's API and Twitter as a platform must be addressed. These are, on the one hand, institutional concerns due to the lack of transparency of Twitters Rest API and, on the other hand, the general limitations of the API, which prevented this thesis from collecting more meaningful data. One way to make better use of the collected data, for example to find users acting between the conspiracy networks, would have been to create a friend-follower network. This way, the global level of users with conspiracy beliefs could have been better captured. A similar methodological approach was used in a study by González-Bailón & Wang (2016). However, assuming that no user follows more than 5000 users (each API call returns up to 5000 friends for 15 users every 15 minutes) it would have taken about 104 days to gather the friends of the 150,000 users who have tweeted or retweeted conspiracy theory content. This approach was not feasible in the context of this thesis. The second limitation is that the methodology used may not have been able to capture every conspiracy theory as a whole. Due to the keyword selection process, only tweets were collected that either directly mentioned the conspiracy theory or contained related terms. This excluded tweets that contained conspiracy related information in videos or images, and tweets that simply did not use the selected keywords but still referred to conspiracy theories. On the other hand, it is possible that some of the data collected was actually not from users who believe in conspiracy theories, but rather from, for example, a debunking community or a sarcastic group of users who use the terms in a humorous way. Besides the process of keyword selection itself, the only countermeasure taken to prevent this was to use only the main component for the analysis. At this point in particular, however, a more thorough qualitative approach might have been more appropriate. Another limitation imposed by the chosen methodology is that most of the results of this work are merely of a correlating nature.The third and biggest limitation is the decision itself to analyze Twitter networks. All results of this thesis are limited to the Twitter sphere and should only be interpreted as such and not beyond it. After all, the general spread of conspiracy theories happens only to a very limited extent through tweets, retweets, @-mentions and replies. Conspiracy theories are cross-platform and manifest themselves in videos, images and text not only on Twitter and other online social networks, but also in alternative media and personal networks, be they WhatsApp groups or bowling clubs.

11 Conclusion

This thesis offered a deeper insight into the network mechanics and the role of opinion leaders in conspiracy networks on Twitter. It was also able to show that the distinction between conspiratorial and ideological predispositions not only determines which group of people are attracted to them, but that networks formed around conspiracy theories with ideological elements differ in structure and user base from networks formed around conspiracy theories without ideological elements. Furthermore, it could be shown that at least the four conspiracy theories examined receive only mediocre attention on Twitter, and that the majority of users show relatively little interest in conspiracy theories and that this interest is mostly limited to one conspiracy theory.

Further research is needed that opens up the field of research beyond Twitter and considers other platforms and media forms. Opinion leaders, with varying degrees of importance, will always play a role in the dissemination of information, so looking beyond Twitter could reveal information resources of people who believe in conspiracy theories and show how opinion leaders bring new information into existing networks. Furthermore, the results of this thesis suggest that there is a small user group that is very active and acts as both local and global opinion leaders. Case studies of these users over longer periods of time could also show how these users adapt new conspiracy theories and how they disseminate new information in their networks.

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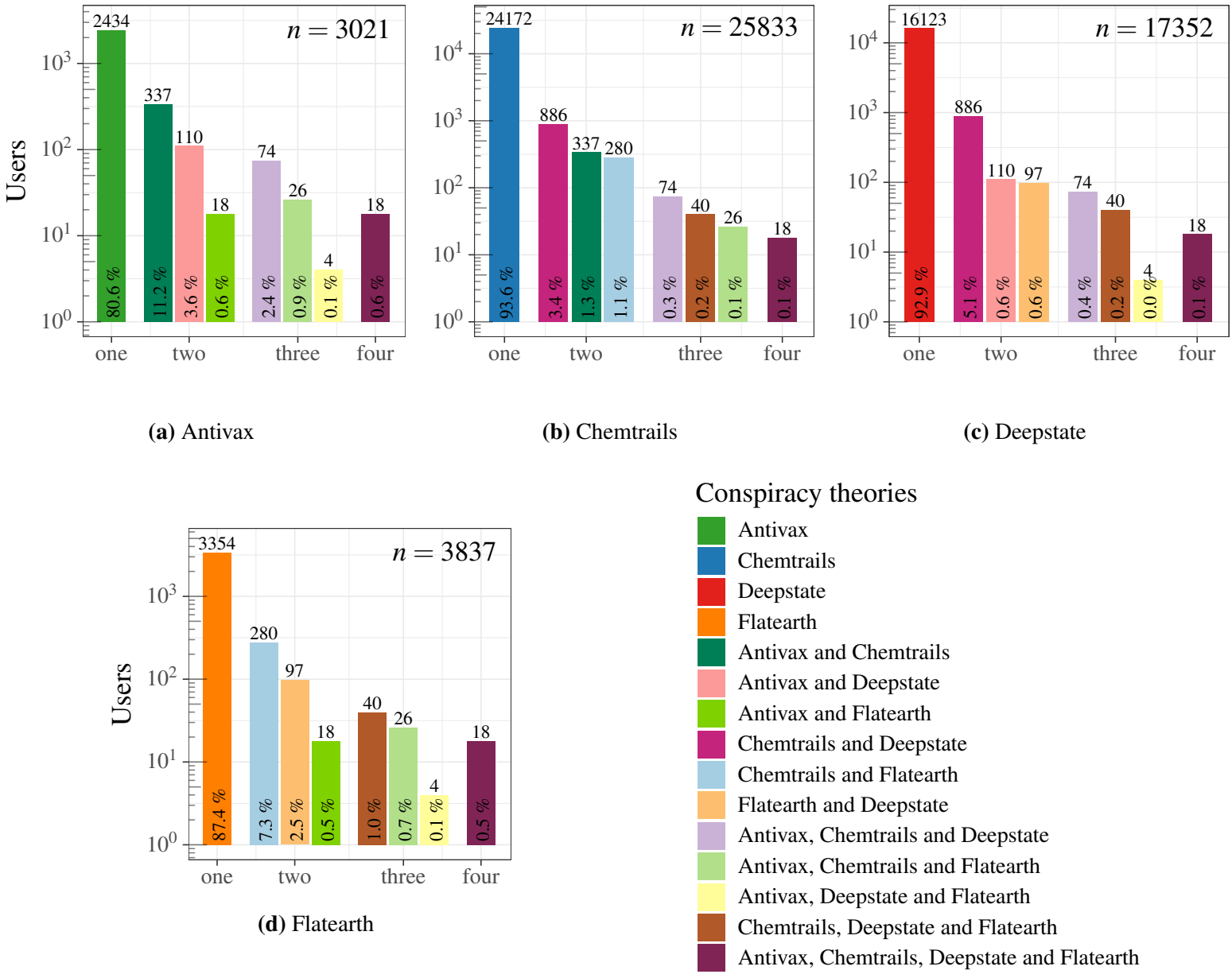
Appendices

A Distributions

A.1 Tweet activity distribution

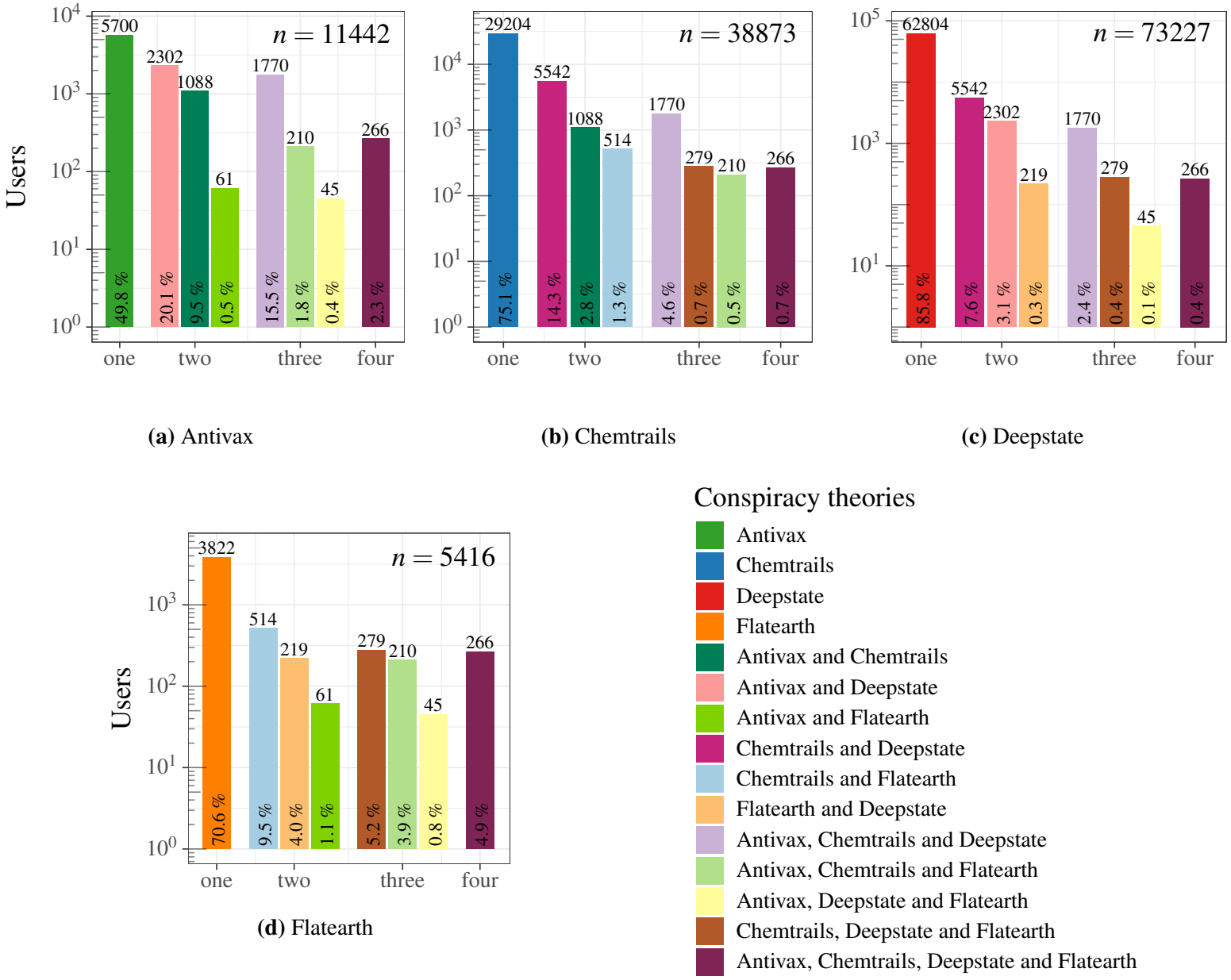


(a) Antivax **(b)** Chemtrails **(c)** Deepstate

(d) Flatearth

Figure 5: Distribution of tweet activity for each conspiracy theory

A.2 Retweet activity distribution

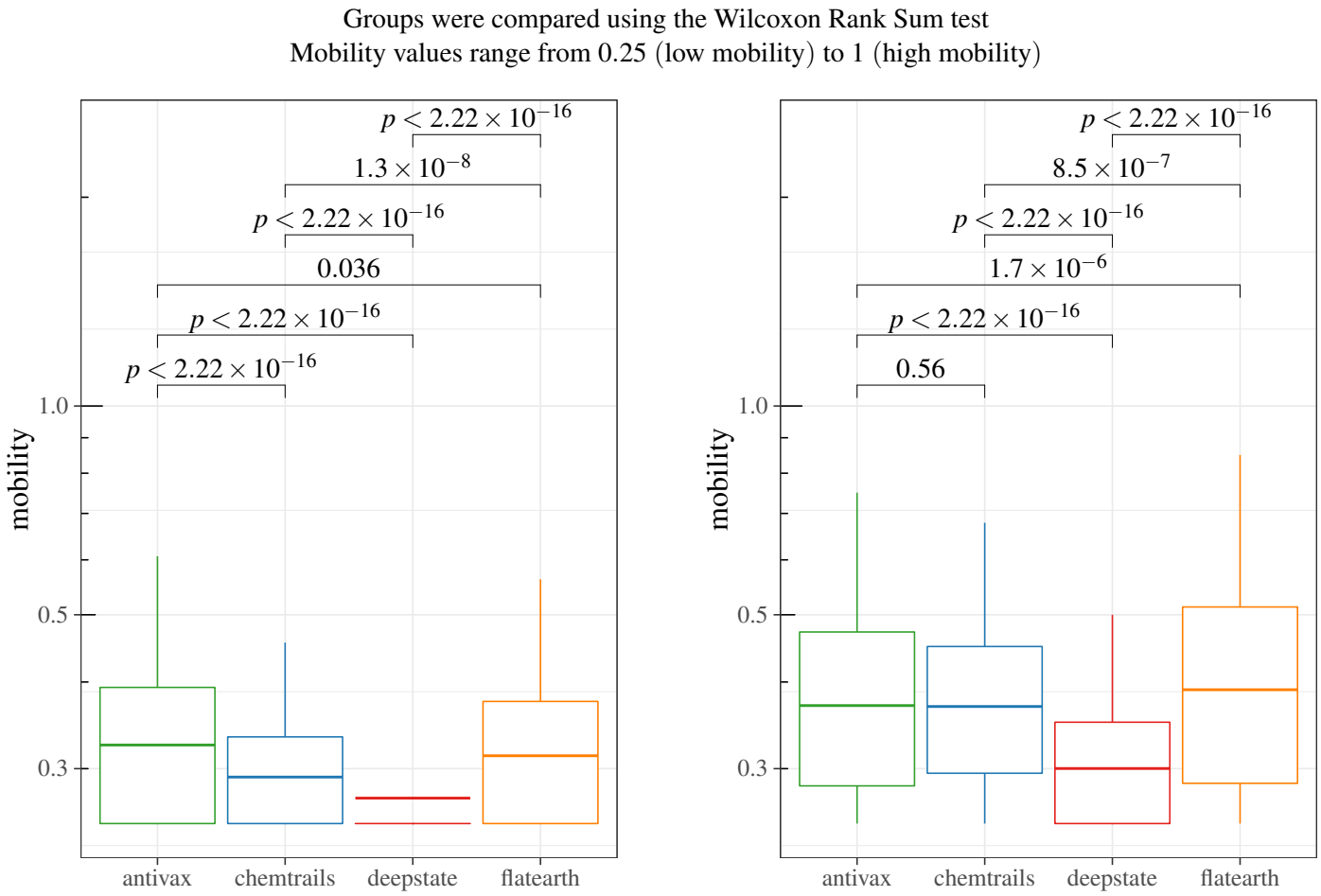


(a) Antivax **(b)** Chemtrails **(c)** Deepstate

(d) Flatearth

Figure 6: Distribution of retweet activity for each conspiracy theory

A.3 Mobility distribution



(a) Tweets

(b) Retweets

Figure 7: Mobility distribution for each conspiracy theory

B Graph-level network analysis

B.1 Network structure @-mentions networks

Conspiracy theory network	Nodes	Edges	Density	$N_{Communities}$	Q
Global	11 842	68 766	4.9×10^{-4}	128	.75
Antivax	1424	9673	4.8×10^{-3}	33	.48
Chemtrails	6450	24 619	5.9×10^{-4}	83	.75
Deepstate	4360	10 818	3.4×10^{-2}	57	.72
Flatearth	1103	22 723	3.3×10^{-1}	27	.40

Table 6: Network structure of the @-mentions networks

B.2 Network structure retweet networks

Conspiracy theory network	Nodes	Edges	Density	$N_{Communities}$	Q
Global	114 175	363 330	2.8×10^{-5}	459	.60
Antivax	11 300	59 044	4.6×10^{-4}	120	.53
Chemtrails	36 382	73 355	5.5×10^{-5}	409	.75
Deepstate	73 624	208 204	3.8×10^{-5}	137	.51
Flatearth	6532	21 541	5.0×10^{-4}	112	.63

Table 7: Network structure of the retweet networks

C Node-level analysis

C.1 Local opinion leadership correlations

C.1.1 Local brokerage @-mentions network

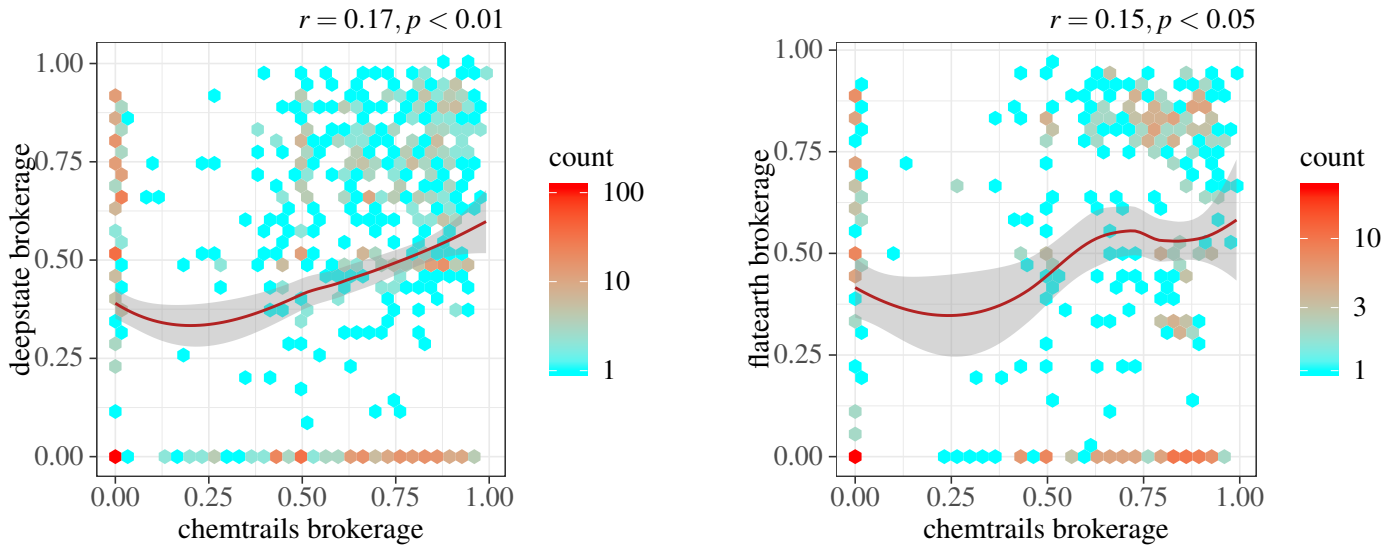


Figure 8: Scatter plots of significant brokerage correlations in the @-mentions networks with a value above 0.1

C.1.2 Local brokerage retweet network

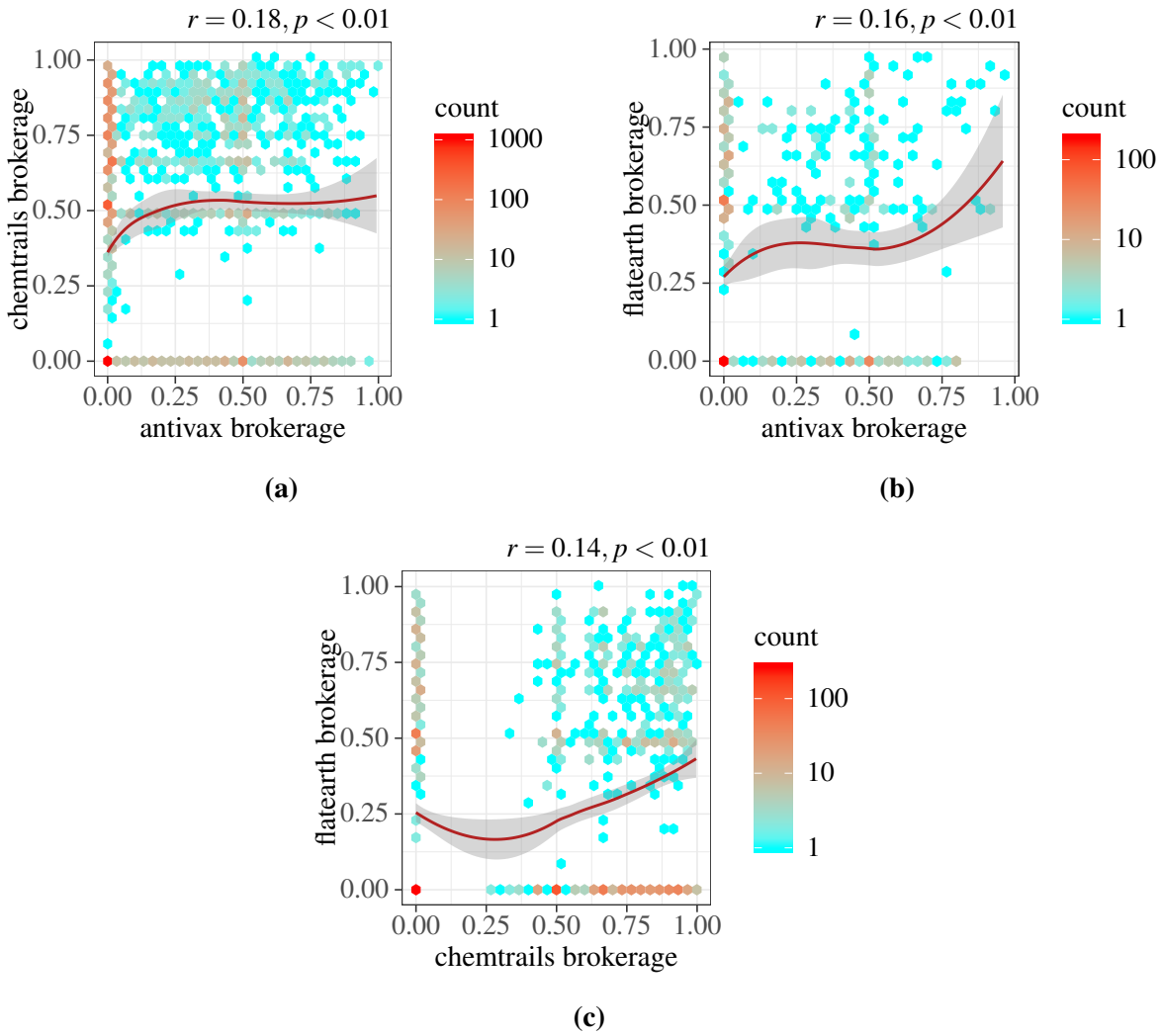


Figure 9: Scatter plots of significant brokerage correlations in the retweet networks with a value above 0.1

C.1.3 Local visibility @-mentions network

@-mentions network in-degree	M	SD	1	2	3	4
Antivax	4.8×10^{-3}	1.6×10^{-2}				
Chemtrails	5.9×10^{-4}	2.9×10^{-3}	0.03			
Deepstate	5.7×10^{-4}	2.9×10^{-3}	-0.04	$.08^{*}$		
Flatearth	1.7×10^{-2}	5.9×10^{-2}	-0.10	.05	.01	

$^{*}p < .05, ^{**}p < .01$

Table 8: Visibility correlations for the @-mentions networks

C.1.4 Local visibility retweet network

Retweet network in-degree	M	SD	1	2	3	4
Antivax	4.6×10^{-4}	3.7×10^{-2}				
Chemtrails	5.5×10^{-5}	9.0×10^{-4}	$.44^{**}$			
Deepstate	3.8×10^{-5}	1.1×10^{-3}	.01	$.04^{**}$		
Flatearth	5.0×10^{-4}	4.8×10^{-3}	.05	.04	.02	

$^{*}p < .05, ^{**}p < .01$

Table 9: Visibility correlations for the retweet networks

C.2 Global opinion leadership correlations

C.2.1 Global and local brokerage @-mentions networks

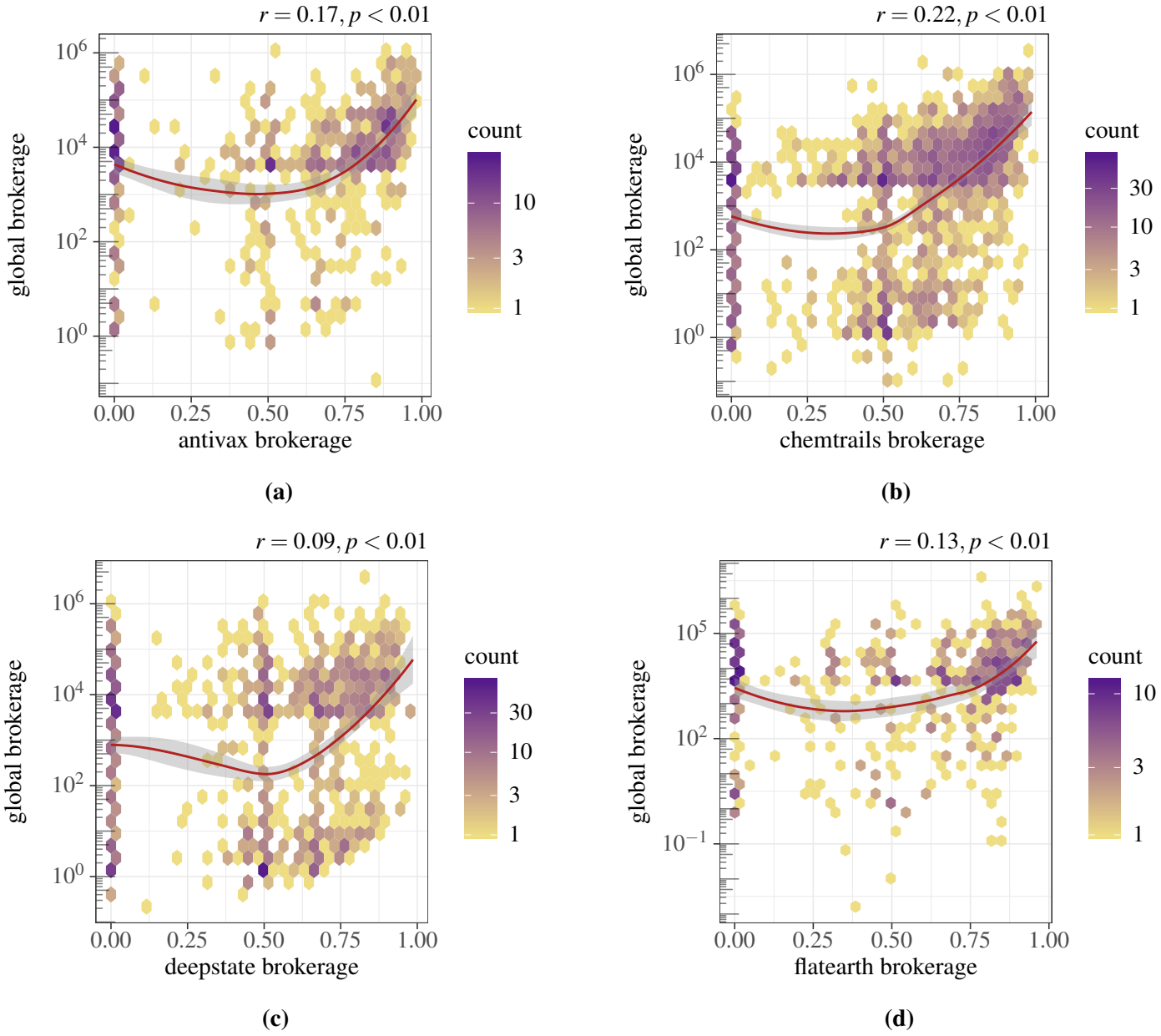


Figure 10: Scatter plots of global and local brokerage in the @-mentions networks

C.2.2 Global and local brokerage retweet networks

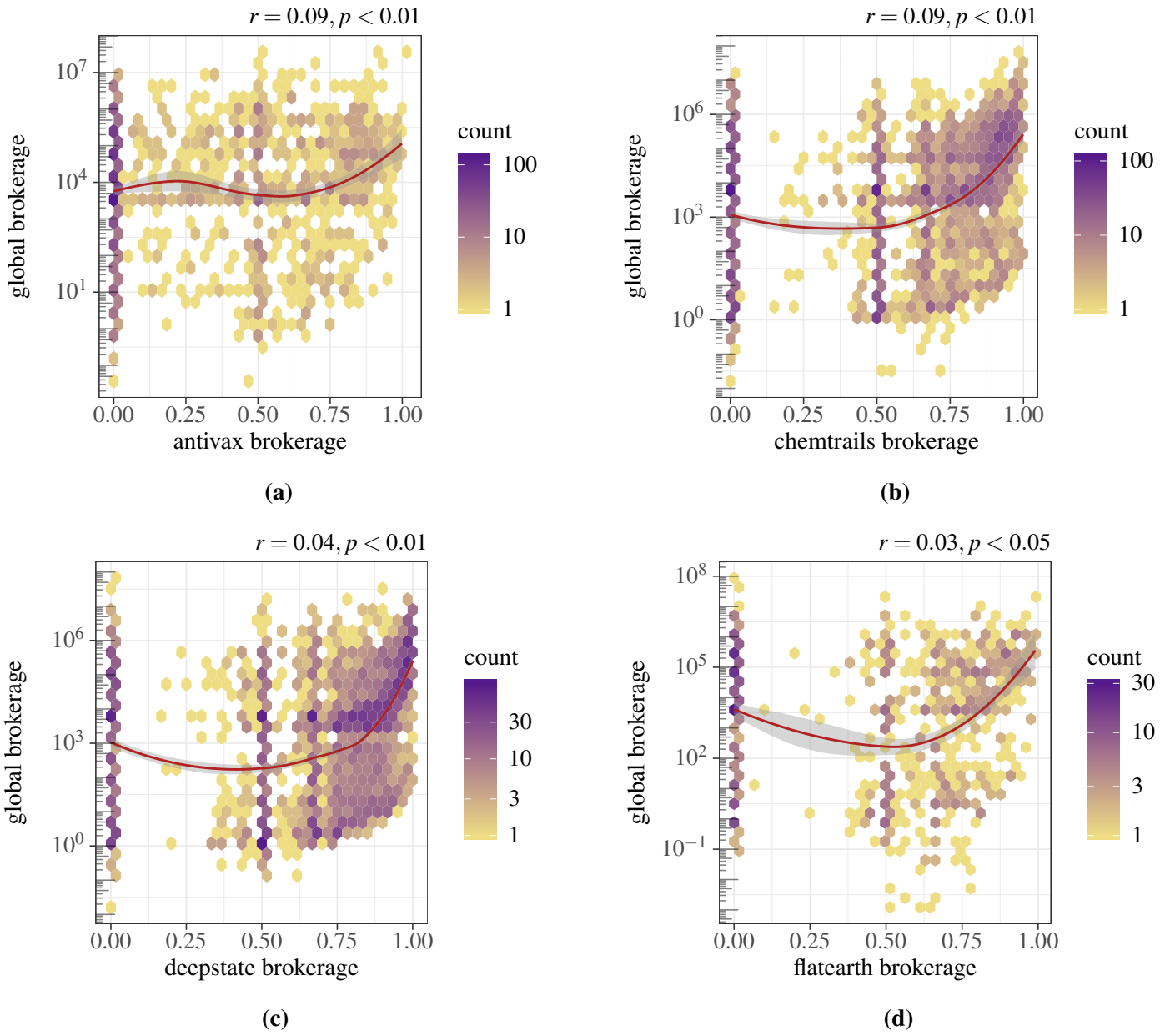


Figure 11: Scatter plots of global and local brokerage in the retweet networks

C.3 Opinion leadership and visibility

C.3.1 Mentions and retweets received

@-mentions network brokerage	Received mentions
Global	$.27^{**}$
Antivax	$.37^{**}$
Chemtrails	$.28^{**}$
Deepstate	$.23^{**}$
Flatearth	$.38^{**}$

$^{*}p < .05, ^{**}p < .01$

(a) Visibility correlations for the @-mentions networks

Retweet network brokerage	Received retweets
Global	$.04^{**}$
Antivax	$.04^{**}$
Chemtrails	$.17^{**}$
Deepstate	$.07^{**}$
Flatearth	$.20^{**}$

$^{*}p < .05, ^{**}p < .01$

(b) Visibility correlations for the retweet networks

Table 10: Correlation between opinion leadership and visibility as in-degree centrality

Retweet network in-degree	Total tweets
Global	0.50^{**}
Antivax	0.95^{**}
Chemtrails	0.40^{**}
Deepstate	0.08^{**}
Flatearth	0.56^{**}

$^{*}p < .05, ^{**}p < .01$

Table 11: Correlation between the number of retweets and the number of total tweets

C.3.2 Number of followers and brokerage

@-mentions network brokerage	Number of followers
Global	$.08^{**}$
Antivax	.02
Chemtrails	$.08^{**}$
Deepstate	$.14^{**}$
Flatearth	$-.04$

$^{*}p < .05, ^{**}p < .01$

(a) Visibility correlations for the @-mentions networks

Retweet network brokerage	Number of followers
Global	$.01^{**}$
Antivax	$.04^{**}$
Chemtrails	$.07^{**}$
Deepstate	.01
Flatearth	.02

$^{*}p < .05, ^{**}p < .01$

(b) Visibility correlations for the retweet networks

Table 12: Correlation between opinion leadership and visibility as number of followers

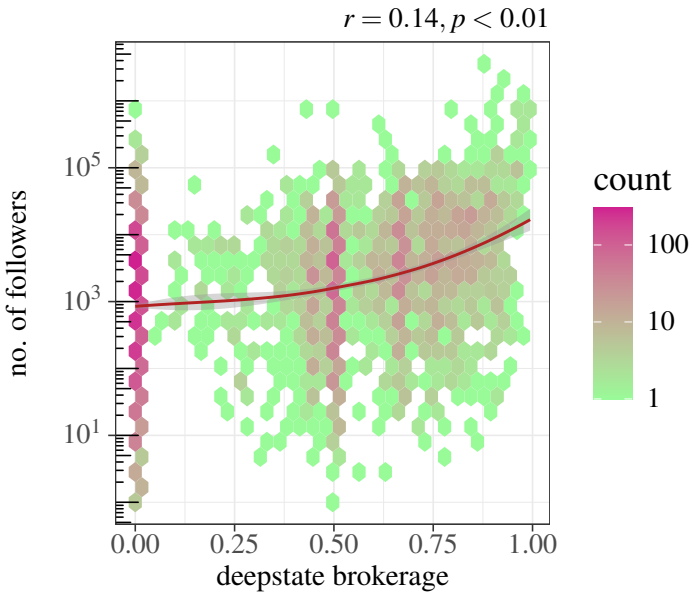


Figure 12: Correlation between the number of followers and brokerage in the deepstate @-mentions network

C.4 Opinion leadership and mobility

@-mentions network brokerage	Tweet mobility
Global	$.06^{**}$
Antivax	$-.07$
Chemtrails	$-.02$
Deepstate	$.01$
Flatearth	$-.10^{*}$

$^{*}p < .05, ^{**}p < .01$

(a) Mobility correlations for the @-mentions networks

Retweet network brokerage	Retweet mobility
Global	$.11^{**}$
Antivax	$-.16^{**}$
Chemtrails	$.10^{**}$
Deepstate	$-.28^{**}$
Flatearth	$-.20^{**}$

$^{*}p < .05, ^{**}p < .01$

(b) Mobility correlations for the retweet networks

Table 13: Correlation between opinion leadership and mobility