Lund University
Faculty of Social Sciences
Department of Political Science

Bachelor Thesis
Political Science: Bachelor's Course (STVK02)
Spring, 2019

Soros, Sentiment, and Polarisation

—

Illuminating Confirmation Bias in Conspiracy Theory Belief

Leon S. Klingborg

Supervisor:
Maria Hedlund, Ph.D. Senior Lecturer

May 16, 2019

Abstract

Recently, conspiracy theories have gotten more attention for their potential role in the political arena. Although some claim that conspiracy theories serve important functions, they have been found to be connected to lower intents of political participation. With the rise of the internet they have also been connected to polarisation of attitudes. This paper makes use of the finding that conspiracy theorists tend to polarise in their attitudes and looks at whether or not this is reflected in the sentiment of their online communication. To do this, tools for quantitative sentiment analysis are employed and discrete time-series regression models are estimated using communication about conspiracy theories connected to George Soros on Twitter. The paper also tries to distinguish which of the explanations for attitude polarisation proposed in contemporary literature are at play in this specific context. The results indicate that there is a strong tendency of sentiment polarisation among conspiracy theorists as they interact with conspiracy theories. Contemporary literature suggests that the explanation for such a relationship could be either confirmation bias in evaluating information or social dynamics making individuals conform towards the extremes. This paper finds only limited indications for the social dynamics proposed.

Keywords: conspiracy theories, attitude polarisation, sentiment analysis, George Soros, biased assimilation, Twitter API.

Words: 9666

Contents

1 *Introduction*

Most people have at some point encountered a conspiracy theory. Conspiracy theories seem to exist in all corners of the world and are most of the time somewhat controversial and even stigmatised. This is well illustrated by the fact that people not predisposed towards believing conspiracy theories express fear of social exclusion when tasked with writing about evidence of conspiracy theories (Lantian et al. 2018, p. 939). However, belief in conspiracy theories is nonetheless widely spread. In a study by Oliver and Wood (2014, p. 952), it was found that about half of the American public believes in at least one major conspiracy theory.

Being a reoccurring phenomenon, present in many different aspects of society, conspiracy theories have spurred interest from several angles. One such angle is conspiracy theories as expressions of power dynamics and politics, in one way or another interfering with core institutions and values. This has produced a variety of perspectives on the danger, but also the possible utility of conspiracy theories, especially for democracy and formation of public opinion (Douglas et al. 2019, p. 17).

Some theorists claim that conspiracy theories serve the function of offering a channel through which established norms and values can be questioned and thereby are of use to a democratic process. This is thought to especially be the case for marginalised groups (Moore 2016, p. 8; Grewal 2016, pp. 39–41; Miller 2002, pp. 51–54). However, belief in conspiracy theories has been shown to be related to distrust in public institutions, to decreased intentions of engaging in political activities, to extreme political ideologies, and to a higher acceptance of violence as a political tool (Lee 2017, pp. 16,17; Einstein and Glick 2015, pp. 696–698; Bartlett and Carl 2010, pp. 29–32). These are by no means what is usually regarded as characteristics of a healthy democracy, raising doubts about the virtue of conspiracy theories.

In recent times, with the rise of the internet, the relevance of studying conspiracy theories can be argued to have increased. Today, there is a vibrant discussion about the possibilities and dangers of public debate and discourse online. On the one hand, there is talk about increased opportunities for ideas to spread and for democratic deliberation to take place. On the other hand, there are indications of polarisation through 'echo-chambers' and of hate speech by 'trolls' (Bessi et al. 2015c, pp. 1–3; Bessi et al. 2015b, p. 10). Concern has been put forward that negative sides of digitalisation might be especially prevalent for online communities built on conspiracy theory belief (Bessi et al. 2015a, 554–558).

To really reach clarity regarding how conspiracy theories should be understood in the context of democracy and the formation of public opinion, it is essential to put together a thorough account of their causes and consequences. Building on previous research on the causes of conspiracy theories, this paper aims to contribute to an account of consequences of conspiracy theories. Specifically, this paper looks to theory mainly from the field of political psychology to understand mechanisms connected to the exposure to, and interaction with, conspiracy theories online, particularly mechanisms affecting the tone of related discourse.

1.1 Research Question

This section presents the specific research question of the paper. The broad aim, which was presented in the introduction, is narrowed down significantly and connected to theoretical concepts not yet thoroughly introduced. Relevant background to fully understand the research question is presented in sections 2 and 3.

One important concept for understanding conspiracy theories has turned out to be *attitude polarisation*. Further, an important tool for understanding the tone of communication is the concept of *sentiment*. This paper brings these two together and asks what attitude polarisation does to the sentiment of online communication about conspiracy theories.

> **Research Question:** What are the effects of attitude polarisation on the communicated sentiment of individuals promoting conspiracy theories online?

As is made clear from Section 3, the analysis attempting to answer the question is based on data extracted from individuals posting about conspiracy theories about George Soros on the online social media platform Twitter.

1.2 What is a Conspiracy Theory?

To make the aim of the present study fully understandable it is necessary to present a clear distinction as to what is to be studied and what is not. In other words, what is regarded as a conspiracy theory?

In everyday usage, the meaning of 'conspiracy theory' can be somewhat indistinct. Often it is thought of as theories which are straight out false, other times it is seen as a way of understanding events in the world as being caused by malicious and powerful individuals. This paper is not limited to any one of these, instead the definition draws on both thoughts to try and capture a general phenomenon. The definition, which applies for all subsequent mentions of conspiracy theory, is inspired by how it is most of the time defined in existing literature and can be phrased as follows: A conspiracy theory is a story about how certain bad events or phenomena have come about, it claims that they have come about as a consequence of powerful individuals in covert cooperation and the claim is based on alleged knowledge that has been generated by unconventional means (that is, not by scientific neither by otherwise accepted methods of establishing knowledge) (see Douglas et al. 2019, pp. 4,5).

2 *Understanding Conspiracy Theories*

2.1 State of the Literature

Contributing to the contemporary account of causes and consequences of conspiracy theories means finding an angle which is yet unexplored in the literature. To pinpoint this angle it is necessary to present an overview of how far scholars have already come in their knowledge generating efforts. In recent times a considerable amount of research has been conducted on conspiracy theories. A lot of energy has been put towards identifying the causes of conspiracy theories whereas less attention has been paid on understanding their potential consequences and the ways in which they are communicated (Douglas et al. 2019, p. 23). The following subsections briefly summarise relevant findings of contemporary conspiracy theory research and specify where this paper fits in the overall literature on the topic.

2.1.1 Causes of Conspiracy Theory Belief

Looking at the research on the causes of belief in conspiracy theories, a broad range of factors have been considered and shown to be significant predictors. Taken together, a rather complex picture reveals itself with psychological, demographic, as well as political factors.

The psychological factors can be broken down into different types of motives for believing in conspiracy theories, including epistemic motives, existential motives and social motives (Douglas et al. 2019, pp. 6,7; Douglas et al. 2017). Epistemic motives arise when individuals feel a need to understand their surroundings. This need has in turn been shown to be greater for meaning-seeking individuals, under conditions of uncertainty, concerning important and large scale events, and for individuals who want closure related to a traumatic event (Van Prooijen and Jostmann 2013, pp. 113,114; Van Prooijen and Douglas 2017, pp. 329,330; Van Prooijen et al. 2018, pp. 331,332; Leman and Cinnirella 2013, pp. 7,8). However, it has also been shown that belief in conspiracy theories can be predicted by tendencies to overestimate the likelihood of specific chains of events, of lower levels of analytic and rational thinking as well as intelligence, to attribute unwarranted agency, to have unwarranted beliefs, and of biased assimilation (the tendency to credit evidence higher the more it confirms ones already established view) (Vitriol and Marsh 2018, pp. 964–967; Leman and Cinnirella 2013, pp. 7,8; Dagnall et al. 2017, pp. 7–11; Mikuskova 2017, pp. 699,700; Douglas et al. 2016, pp. 69–71; McHoskey 1995, pp. 405–408; Lobato et al. 2014, p. 624). This suggests that conspiracy theories are an alternative for those who have trouble making use of conventional means of knowledge production

(Douglas et al. 2019, p. 8).

Relating to another type of psychological need, existential motives for believing in conspiracy theories have also been identified (Douglas et al. 2017, p. 539). These motives come from feelings of lack of control and of threatened existential needs (Douglas et al. 2019, pp. 8,9). By explaining reality with the help of conspiracy theories, some of the anxiety connected to this is thought to be remedied, in turn explaining the relationship. Belief in conspiracy theories is stronger among individuals experiencing feelings of powerlessness, lack of control and alienation from society, specifically in socioeconomic contexts (Abalakina-Paap et al. 1999, p. 637; Goertzel 1994, p. 731).

A third type of motivation for believing in conspiracy theories can be categorised as social motives (Douglas et al. 2017, p. 540). Belief in conspiracy theories can, firstly, be a way for individuals to keep a positive self-image. There is evidence in line with this theory connecting narcissism to belief in conspiracy theories (Cichocka et al. 2016, p. 157). Secondly, conspiracy theories can serve the function of distinguishing the individual from the crowd. Individuals who believe in conspiracy theories more frequently express a need to feel unique, relative to the general public (Imhoff and Lamberty 2017, p. 724). Another social function of conspiracy theories is connected to group identities. Individuals are more likely to believe in conspiracy theories if they suggest that their own group is oppressed or if another group is supposedly responsible (Cichocka et al. 2016, p. 161). The effects are greater for groups which have historically experienced discrimination or oppression, that is, often times, low-status groups (Simmons and Parsons 2017, pp. 585,595).

Moving on, demographic factors explaining the spread of conspiracy theories have also been identified. Demographic factors identified as predictors of conspiracy theory belief are: sex, men are more frequent than women; education, highly educated individuals are less frequent; wealth, poor individuals are more frequent; employment, unemployed are more frequent; ethnicity, members of minority ethnicities are more frequent; and social status, individuals with a smaller social network are more frequent among conspiracy theory believers (Freeman and Bentall 2017; Goertzel 1994; Simmons and Parsons 2017). Direct causality is however not always claimed, often these factors are instead regarded as being mediated by psychological causes (Van Prooijen 2017, p. 50).

Just like demographic factors, political factors behind belief in conspiracy theories are often thought to be mediated by psychological effects. It is, for example, easy to see how feelings of powerlessness or states of uncertainty could arise as consequences of political events. Political factors have been shown to play important roles for conspiracy theories and their spread; political scandals, elections, and extensive media coverage are all related to higher belief in conspiracy theories (Einstein and Glick 2013, pp. 24,25). The political arena, thereby, is essential for understanding what the effects of conspiracy theories might be on society as a whole.

One reoccurring finding is that individuals believe in conspiracy theories based on what political view they have; conspiracy theories framing political opponents as conspirators are generally favoured (Edelson et al. 2017, p. 933; Claassen and Ensley 2016, p. 317; Smallpage et al. 2017, p. 4,5). However, conspiracy belief in general is higher on political fringes (Van Prooijen et al. 2015, p. 570). Some studies also show that conspiracy theories are more common to the right of the political spectrum and it is suggested that the explanation might be that people on the right often share the personality characteristics which are thought to cause belief in conspiracy theories (Jost et al. 2003, p. 339; Douglas et al. 2019, p. 11; Nefes 2013, pp. 259–261). The tendency of believing conspiracy theories supportive of the political stance of the individual has been observed rather closely in contexts of evaluation of information and evidence. When faced with information about a conspiracy theory, more often than not, it is interfered as supportive of the present view, no matter the characteristics of the information (Claassen and Ensley 2016, pp. 332,333; Jerit and Barabas 2012, p. 672). There is, in other words, a strong confirmation bias making the predisposed position very robust, even to facts which apparently contradicts it.

This paper builds on a couple of key notions taken from above-presented findings. To begin with, it can be said that conspiracy theories serve as a refuge for individuals who are not content with the established view of some aspect of the world. From the findings presented above, this discontent seems to have many origins. Some of these origins seem to have to do with specific events, affecting individuals to seek comfort in alternative explanations. Other sources of discontent with established world views seem to have more to do with the personality of the individual, such as their level of analytic thinking, feeling of alienation, or need to feel unique.

No matter the reason, conspiracy theorists clearly put up robust barriers protecting their convictions from what others would consider to be true facts, information which if seriously considered would challenge the conspiracy theory. These barriers are evident in the tendency of conspiracy theorists to credit evidence confirming their own views higher than evidence debunking the same. In psychology literature this tendency is called biased assimilation and is one of the causes of attitude polarisation. Attitude polarisation is the tendency of individuals to move towards the extreme of a previously more moderate view on a particular question (Lord et al. 1979, p. 2098). As was stated above, conspiracy theory believers have even been observed to find evidence discrediting a conspiracy theory to confirm the same theory, against all conventional reason (Claassen and Ensley 2016, pp. 332,333; Jerit and Barabas 2012, p. 672).

Additionally, the barrier that conspiracy theorists put up against the surrounding world seems to have a strong social dimension. Conspiracy theories can both serve a social function for an entire group discontent with established world views, for example low-status groups. However, conspiracy theories can also serve a social function by bringing alienated individuals together, thereby forming new social networks within which these individuals can keep their positive self-image by recognising each others' views (Cichocka et al. 2016, p. 161).

2.1.2 Conspiracy Theorist Behaviour

From Section 2.1.1 it is clear that there is a complex pattern of causes and predictors of conspiracy theory belief and that these have a lot of bearing on politics and society in general. The paper now turns to the consequences of conspiracy theory belief, specifically how belief in conspiracy theories affect how conspiracy theories are talked about in the public sphere and implications for political behaviour. It is worth noting that most research on the consequences of conspiracy theory belief is based on correlation only. Therefore in many cases, the conclusions are hard to generalise as definitely being consequences, what is more certain is that they describe the behaviour of conspiracy theorists (Douglas et al. 2019, p. 20) .

In most of the instances where effects of belief in conspiracy theories have been observed, they are very much in line with what one would expect based on what has already been established to be causes of conspiracy theory belief. For example, when individuals communicate information insinuating a conspiracy it is likely to be one that is in line with their political views (Nefes 2013, pp. 255–258). This behaviour has further been shown to be magnified when important political events, such as elections, are taking place. Communicating information suggesting conspiracies might then be thought of as a way for the individual to give voice to their views and values (Raab et al. 2013, pp. 6–8). This has especially been the case when such views challenge established norms and hierarchies (Sapountzis and Condor 2013, p. 731). Coherent with another of the previously mentioned causes of belief in conspiracy theories, communicating conspiracy theories has been argued to fulfil the symbolical role of making sense of chaotic or threatening events for affected groups or communities; conspiracy theories become a part of the in-group narrative and discourse (Franks et al. 2013, pp. 9,10). A more troubling effect of conspiracy theory belief is that it seems to decrease trust in public institutions (Einstein and Glick 2015, p. 679).

Regarding the communication of conspiracy theories, something that has been touched upon from several perspectives is the potential importance and effect of digitalisation and the internet. Contemporary literature is indecisive on whether or not the internet has made conspiracy theories more or less viable (Douglas et al. 2019, p. 15). No matter the correct answer, a lot of information about conspiracy theories and the social interactions surrounding it is mediated through online platforms, making it relevant to study specifically. The main point of the studies pointing to this has been that online communities, and especially those revolving around conspiracy theories, tend to polarise, creating so-called 'echo-chambers' where there is little interaction across communities (Bessi et al. 2015b). Resulting communities connected to conspiracy theories have also turned out to be active and socially inclusive (Grant et al. 2015). In the instances when conspiracy theorists do clash with individuals of opposing beliefs the consequent discussions have been shown to become more negative in their sentiment as they progress over time (Zollo et al. 2015, pp. 10,11). Conspiracy theorists also have a more negative sentiment overall (Zollo et al. 2015, pp. 10,11). At the same time, there is evidence that they make an effort to appear credible and factual (Wood and Douglas 2015, pp. 7,8).

Specific conspiracy theories are also associated with specific behaviours. As an example, intentions of political participation, such as voting, are lower among believers of anti-establishment conspiracy theories (Jolley and Douglas 2014, p. 35). Research suggests that these mechanisms are used by extreme political movements in their rhetoric, building their narrative, strengthening the effects of radicalisation processes (Bartlett and Carl 2010, pp. 29–32). Related, conspiracy theories are used as arguments for political violence by extremist groups (Lee 2017, pp. 16,17).

Something that supports the theory of biased assimilation specifically for conspiracy theories, first mentioned in Section 2.1.1, is that conspiracy theorists have been observed to often share and spread information which is clearly false and even produced to be sarcastic (Bessi et al. 2015a, pp. 1–4). The mechanism of biased assimilation, thereby, occasionally seems to be so strong that factual inconsistencies are completely overlooked by conspiracy theorists in their communication.

Also on this end of the literature there are certain aspects of particular interest to this paper. First of all, it adds to the relevance of the aim of the paper that there is a clear relationship between conspiracy theory belief and political behaviour. The finding that conspiracy theorists are less inclined to engage politically is based on robust experiment-based research. (It should, however, be mentioned that there are indications that the opposite might be true under certain conditions (Imhoff and Burder 2014, p. 24).) Second, many scholars have focused on the communication of conspiracy theories and what governs it, correctly identifying that conspiracy theories rely on communication for their spread since they in their essence are immaterial. To understand dynamics behind this communication, some have looked at the tone of online conspiracy theory related communication and one study in particular by Zollo et al. (2015, pp. 11–13) has done so by employing quantitative sentiment analysis.

2.1.3 Implications of Existing Literature for the Present Paper

Connecting this brief literature review back to the research question, a couple of things can be underlined. To begin with, there is evidence suggesting that there are substantial consequences of conspiracy theories and conspiracy theory belief. Specifically, these are not seldom closely related to political positions and movements, particularly on the fringes and the extremes.

Consequences which have been identified so far have further been connected to both attitude polarisation and online sentiment, showing that both these concepts are important for understanding conspiracy theory belief. For example, in a study by McHoskey (1995), individuals who had a prior tendency of believing in conspiracy theories, to a larger extent than a control group, strengthened their beliefs after being exposed to material suggesting the existence of conspiracies. In essence, this research suggests that individuals who already adhere to conspiracy theory belief, and who are continuously exposed to information about conspiracy theories, on average are strengthened in their beliefs. This is thought to be true no matter if the information is supportive or sceptical, and it is explained with the help of psychological polarisation effects.

In a study using data from Facebook, Zollo et al. (2015, pp. 10,11) showed that discussions about conspiracy theories—comments on Facebook pages' posts relating to conspiracy theories—had a tendency to develop a more negative sentiment as they progressed. The tendency was also significantly greater for discussions about conspiracy theories than it was for discussions about science.

This is an indicator that polarisation effects might be effective in explaining variation in online sentiment, something that if shown would consolidate and advance contemporary understanding of consequences and communication of conspiracy theories. The relative scarcity of studies on potential consequences also makes it relevant to make an entry to this body of research. In Section 2.2, the theory of attitude polarisation is presented in more depth and in Section 2.3 applied to explain polarisation of sentiment among conspiracy theory believers.

2.2 Attitude Polarisation

Previous research, presented in sections 2.1.1 and 2.1.2, has indicated that belief in conspiracy theories is related to both polarisation and online sentiment. This paper aims to bring these two concepts together by explaining online sentiment among conspiracy theorists with the help of polarisation, thereby adding to the understanding of the dynamics behind conspiracy theories. Before turning to the specifics of the suggested relationship between sentiment and polarisation, the theory of attitude polarisation is introduced below.

Time and time again scholars have found that groups of individuals who share a certain predisposition towards some issue tend to polarise as they deliberate (Sunstein 2002, pp. 177–180; Myers and Lamm 1976, p. 604). That is, after discussing an issue with one another, the average position is more firmly consolidated than before and is also more extreme. This is thought to be mainly because of two things building on each other. Firstly, it is often explained with the help of the concept homophily, that is, the tendency of individuals to conform to the views of those around them. The social network of an individual as a rule, because of homophily, consists of individuals with similar views (Dandekar et al. 2013, p. 5791; Bessi et al. 2015b). This means that there, most of the time, exists a rather clear bias in a group regarding certain issues; one view is reoccurring. Here, secondly, it is thought that individuals are generally working towards reaching social status in the group, individuals therefore adopt a view which is in line with what is most often communicated, leading to polarisation and consolidation towards the extreme (Sunstein 2002, pp. 183–186; Myers and Lamm 1976, pp. 613–615).

Building on this and adding to the explanation, polarisation has also been observed to be the result of biased assimilation. As can be read in Section 2.1.1, this has been shown to exist in the specific framework of conspiracy theories. Biased assimilation is a type of confirmation bias by which information that supports the individual's view is regarded as more credible than information that rejects the already held view. The proposed explanation for this phenomenon is mainly that individuals subconsciously wish to avoid stress and other implication of being proved wrong. The result is that almost no matter what information individuals are faced with, the view that they held from the start is reinforced and radicalised (Lord et al. 1979; McHoskey 1995; Thorson 2016). In other words, their attitudes are polarised.

Common for all mechanism behind attitude polarisation, then, is that they require extended exposure to, or interaction with, a certain issue, on the level of the individual. The process occurs over time and is dependent on the intensity of the interaction or exposure.

All in all, the case for attitude polarisation—as an important mechanism for understanding conspiracy theories—has considerable support in the literature. The question remaining is what the consequences of polarisation among conspiracy theorists might be, will their radicalised views be reflected in their behaviour, and if so, what will it mean for society more generally? This paper is mainly concerned with the first of these questions and building on the theory of attitude polarisation Section 2.3 suggests a partial answer by outlining three hypotheses.

2.3 Hypotheses

As we have seen, there are many causes of conspiracy theory belief. However, to become relevant they all rely upon conspiracy theories first being communicated. In fact, it could be said that all direct effects of conspiracy theory belief are reliant on how conspiracy theories are phrased and spread. It is therefore reasonable to look at how conspiracy theories are communicated, and how this communication is affected by attitude polarisation.

After establishing the aspect of interest, namely communication of conspiracy theories, the consequent question is what should be expected to happen with the communication as individuals polarise in their attitudes? As was stated above, this paper looks specifically on implications of attitude polarisation on the sentiment—or tone—of communication of conspiracy theories.

Assuming that previous research is correct in the finding that attitude polarisation and both its hypothesised causes—biased assimilation and wish to gain social status—are important mechanisms for conspiracy theory belief, conspiracy theorists should be expected to get more firm in their beliefs over time. The pace of this process should also be affected by how much they interact with the social network of the conspiracy theory and how much they are exposed to information supporting the same theory.

Specifically, it could be reasonable to imagine that attitude polarisation, as measured by interaction with, and exposure to, conspiracy theories, would lead to a more polarised sentiment, as measured by the tone of communication relating to conspiracy theories. This reasoning is summarised in the first hypothesis of the paper:

> **Hypothesis 1 (H1):** *The more individuals interact with conspiracy theories, the more polarised their sentiment when addressing these same conspiracy theories.*

Whereas biased assimilation would be expected to be a factor causing polarisation of attitudes—and in turn for causing polarisation of sentiment—for anyone believing in conspiracy theories, the effect could be expected to be impacted by the social factors and differences in social status. The theory is that polarisation can be a result of individuals who make an effort to gain social status. The effect of interaction with conspiracy theories on online sentiment would then be expected to be greater for someone who is more invested in the social network surrounding the individual conspiracy theory.

This could manifest itself in different ways but it is reasonable to think that someone who gets a lot of recognition for their interaction is more eager to keep themselves up to speed with the general polarisation tendency. This thinking is summarised in the second hypothesis of the paper:

> **Hypothesis 2 (H2):** *The more recognition individuals get for their interaction with conspiracy theories, the greater the effect in H1.*

Building on the same logic, but applying it to a wider context, it is also reasonable to think that someone who is more established online overall is more socially invested, as well as aware of developments and dynamics on the platforms they are present on. Therefore, they could also be expected to be polarised to a larger extent than those who have a more withdrawn online presence. This thinking is summarised in the third hypothesis of the paper:

> **Hypothesis 3 (H3):** *The more established a conspiracy theorist is online, the greater the effect in H1.*

3 *Measuring Polarisation*

To test the hypotheses this paper relies on data gathered from the microblog Twitter. This is because Twitter data lends itself nicely to systematic, automated, quantitative coding and analysis, meaning that the quantity of data included in the study can be vastly larger than what would have been possible with a manual or qualitative approach. The greatest challenge with an automated quantitative approach is finding good and reasonable operationalisations for the concepts described in the theory. In the case of this paper, however, data gathered from Twitter's API (Application Programming Interface) is well suited for measuring core theoretical concepts in the hypotheses, as will be made clear below in sections 3.1 and 3.2.

The data gathered consists of posts about conspiracy theories about George Soros. Looking specifically on conspiracy theories about George Soros is motivated by the relative ease with which this data is extricable, compared to other big conspiracy theories. The details about this choice are presented in Section 3.2.1.

However, before turning to how data is used to measure theoretical concepts it is useful to have a basic understanding of what Twitter is and what kind of data is extricable. This is outlined in Section 3.1 together with a summary of how the data set used in the analysis was accumulated.

3.1 Twitter Data

A term often used to categorise Twitter is 'microblog'. Essentially, it is a site on the internet where you are able to create your own account and to make short text entries, called 'tweets' publicly visible. Every account also has a timeline where other accounts' tweets are displayed. The selection of accounts and tweets are based on whom the user has decided to 'follow'. To interact with tweets made by other users, it is possible to both 'favourite' and 'retweet'. To favourite is a passive sign of approval, whereas retweeting makes a tweet reappear as a retweet to all the retweeter's followers. To put a tweet in a certain context and to reach a certain audience, a tweet can be tagged with a 'hashtag'. The hashtag, in turn, gets its own timeline which other users can choose to interact with. It should be pointed out that there are other mechanisms on the Twitter platform but none that are relevant to the analysis of this paper.

With the help of Twitters own API, it is possible to extract tweets and retweets in neat data sets. It is also possible to, in different ways, filter which tweets get collected. The data sets which are then acquired are organised with the individual tweet or retweet as cases, each containing a variety of data points. The data-points which are most relevant and which are used in this paper are the following: author, text content, time of publication, and the number of favourites and retweets.

The data set that was put together for the purpose of this paper was collected in three steps. First, a large portion of the tweets which were posted under the hashtag #soros between the 31st of Mars and the 10th of April 2019 where collected. (Samples of the sort only go back up to ten days using Twitter's API.) Second, the accounts in the sample which had either posted a tweet or had had a tweet retweeted were identified and their respective most recent 3,200 tweets were collected. (3,200 is the highest number of tweets allowed to be collected from any one account using Twitter's API.) Third, tweets containing the name Soros were filtered out and kept. The emerged data set contains 16,661 tweets from 897 accounts. (For a discussion about the choice of hashtag see Section 3.2.1.)

3.2 Operationalisation of Core Terminology

In order to test the hypotheses, a number of operationalisations of theoretical concepts need to be made. First, it needs to be specified which the conspiracy theories in the analysis are, why they are relevant to look at and how they might be expected to generalise to other conspiracy theories. Second, it needs to be specified how the dependent and the independent variables in the suggested causal relationship, that is, polarity of sentiment and interaction with conspiracy theories, are measured. Necessary clarifications are provided in the subsections below.

3.2.1 Conspiracy Theories – The Case of George Soros

The theories put forward in Section 2.2 are phrased so as to apply to all phenomena which fall under the umbrella of the in Section 1.2 defined conspiracy theory concept. For the sake of efficiently testing the hypotheses however, a sample of theories to be studied needs to be taken. In this paper the analysis is focused specifically on conspiracy theories surrounding George Soros, a Hungarian multibillionaire. George Soros first became known for speculating on currencies in the 1990s. In more recent times, publicity has revolved more around his investments and donations for strengthening democratic institutions and liberal values. This activity has been received in very different light by different actors. Many claim that George Soros is using his wealth to undermine political institutions and that he is doing so by covertly steering a variety of world leaders. Compared to the definition in Section 1.2, such ideas can be argued to be rather clear examples of conspiracy theories.

Conspiracy theories surrounding George Soros are a good pick for reasons connected to both the purpose and the method of this paper. Firstly, these conspiracy theories are arguably the most important present-day example of conspiracy theories with very real political implications. In Hungary, many of them are openly endorsed by the government and used in political campaigning, and in the United States president Donald Trump and members of his staff have openly expressed conspiracy theories about George Soros (Whitfield 2018, pp. 417–420). Secondly, because it is hard to write about these theories without mentioning the name Soros, and because most writings about George Soros on social media seems to be conspiracy theory related—or at least negative—it is easy to automatically identify texts communicating conspiracy theories about George Soros. For these reasons, a study of conspiracy theories about George Soros provides more promising conditions for conducting a clean analysis than what many other conspiracy theories would have offered.

To identify the individuals who make up the networks surrounding conspiracy theories about George Soros, this paper makes use of the frequent occurrence of 'hashtags' in tweets. Hashtags are a way of signalling what a tweet is about. If someone wants to discuss something related to a certain conspiracy theory on Twitter, it is likely that they will include a hashtag that is commonly used by other believers of the theory. By singling out tweets made with these conspiracy theory-specific hashtags, and the accounts that posted them, a measure of the social network can be obtained. The measure does of course come with certain issues, perhaps the most obvious one is that this approach will suffer from both under- and over-coverage. Not everyone who believes in conspiracy theories is active on Twitter and even if they are they might not be under the described types of hashtags. The opposite problem is also to be expected: not everyone active on the hashtags can be expected to believe in the theories. One might be active for their amusement or even to try to debunk the theories. Still, the measure is strong in the sense that it is easily obtainable and consists of data from the real world. The data is thereby protected from being generated as a result of the setting of an experiment, or the wording of a survey. A close reading of a random sample of 100 of the tweets in the data set also reveals that the vast majority are either clearly promoting some sort of conspiracy theory or have a clearly negative view of George Soros.

3.2.2 Interaction with Conspiracy Theories – Discrete Time-Ordering

The suggested way of measuring interaction, with conspiracy theories about George Soros, is to look at tweets which individuals make on the hashtags, specifically the hashtag #soros. Further, every tweet is one of the possibly many made to the hashtag by the same account. These tweets are by necessity ordered in time. To get a measure for how much interaction an individual has had with the conspiracy theory at the time of the individual tweet, all tweets in the data set are equipped with a variable describing which in the order of tweets by the same account a specific tweet is. A possible problem is that tweets containing the name Soros might constitute very different proportions of the interaction with the conspiracy theories for different individuals. Some individuals surely are active consumers of conspiracy theory related content on other sites or even in their real-world activities, whereas others use Twitter more exclusively as a platform for their conspiracy theory belief. The same value on the interaction variable might therefore mean different things for different individuals. With the logic of H1, this would mean that the relationship between sentiment and interaction should be of differing strength based on how much an individual interacts with the conspiracy theory outside of Twitter. It should however still always be positive, meaning that a regression analysis model should still be able to pick up the pattern. As is argued in Section 3.2.5, a part of the dimension of outside interaction might be captured by individuals' follower numbers on their accounts. The number of followers of an account are included as a control variable in the analysis, further remedying the issue.

3.2.3 Polarity of Sentiment – Sentiment Analysis

To measure polarity of sentiment this paper uses sentiment analysis on the text content of tweets. Sentiment analysis aims to measure the sentiment, or tone, of text or speech and can materialise in very different ways. Specifically when analysing political texts, an established direction is to find measurements for positivity and negativity. There are several ways of measuring negativity and positivity, such as hand-coding or use of machine learning algorithms. These methods are however both resource- and time-intensive, rendering them outside the scope of this paper. Instead, the 'bag-of-words' and 'dictionary' approaches are applied.

The bag-of-words approach is a common procedure in quantitative text analysis where the order of words is disregarded. The only thing considered is which words occur, not how they relate to each other. This does, of course, introduce more variance, since data is lost, as well as possible biases from linguistic phenomena such as negation or sarcasm. It does, however, also simplify the analysis to an extent where it is manageable with currently readily available equipment and know-how. Instead of seeing a text as a complex system of meanings and relationships it can be aggregated into frequencies of individual words (Young and Soroka 2012, p. 209).

It is at this point that the dictionary approach is applied. The dictionary approach is simply to let the relevant concept, in this case sentiment in terms of negativity and positivity, be measured by the frequency of a beforehand specified dictionary of words. In this paper the dictionary used is the Lexicoder Sentiment Dictionary which has been shown to successfully be able to measure sentiment in terms of negativity and positivity in political texts by having satisfactory agreement with hand-coded test samples (Young and Soroka 2012, pp. 211–220). The dictionary is composed of a large number of words in the English language, either categorised as negative or positive, no weights of any kind are included.

To create a measurement of sentiment polarity, rather than of negativity or positivity the number of positive and negative words in a tweet are added together. The operationalisation of sentiment polarity, then, is the sum of positive and negative words, as defined by the Lexicoder vocabulary, in each tweet in the data set.

One additional issue, which is present in this specific data set, is that not all tweets are written in the English language. The dictionary used is unable to properly analyse these tweets. The proportion of non-English tweets is fortunately low, based on a closer reading of a random sample it can be estimated to around five per cent. Additionally, these tweets are unlikely to bring with them any systematical biases other than the fact that they will rarely ever be assigned values in other than zero by the automated sentiment analysis. This means that they will only increase the variance and make it harder to identify any relationships between the sentiment variable and any other variable. Therefore, this hardly challenges any relationships which are found despite the fact, meaning that hypothetical evidence in line with the hypotheses reasonably is not weakened.

3.2.4 Social Recognition – Retweets and Favourites

A measure for how much an account has been recognised for its interaction with conspiracy theories—needed for testing H2—can be obtained by looking at favourites and retweets. Most of the time, these functions are meant to signal approval, making them good operationslisations. To get a variable with data for every tweet in the data set, retweets and favourites are first added together. Then, every tweet is given the value of the sum of all retweets and favourites the same account has gotten on its previous tweets in the data set.

3.2.5 Social Establishment – Number of Followers

To test H3, whether a relationship between interaction with conspiracy theories online and sentiment polarisation is magnified by social establishment, the paper needs a measure of how established an individual is online. This is achieved by looking at the follower base of accounts in the data set. Specifically, the number of followers that an account has at the time of tweeting. A high follower count can be expected for individuals and their accounts if they are active and it is reasonable to believe that this, more often than not, corresponds to how socially invested and established they are, at least on Twitter. One potential issue with the measure is that individuals with accounts with high follower numbers also might be different from the average in other ways. For example, high follower counts might be correlated with fame not tied to Twitter, or any online activity. This should however not challenge the validity too much, since they could still be regarded as socially established, just not only on Twitter. Another problem, which needs to be taken into account when interpreting potential results from the analysis is that accounts with high numbers of followers probably are more likely than the average to not represent one individual, but rather some sort of organisation or the like. The data does not allow for an easy control for this meaning that potential differences over this dimension will not be visible in the analysis.

3.2.6 Resulting Variables

With the operationalisations presented above, a collection of variables later used in the statistical analysis, is put together. Descriptive statistics for all these variables are presented in Table 3.1. The first variable in the table is the main dependent variable of the analysis, that is, the operationlisation of sentiment polarity. The variable is referred to as 'Polarity' in the analysis. The following two variables are 'Negativity' and 'Positivity', these are simply the two components of Polarity, namely the number of negative, as well as, positive words in a tweet. The fourth variable, which in the analysis is the main independent variable, is the operationalisation of interaction. Since the variable is based on how tweets from each individual account are ordered in time it is referred to as 'Order'. The fifth variable is the operationalisaton of social recognition. Since it is based on number of retweets and favourites, data points which can be said to describe the spread of a tweet, it is referred to as 'Spread'. The final variable used in the analysis is the operationlisation of social establishment. Since it is based on the number of followers of the accounts it is referred to as 'Followers'.

3.3 Statistical Modelling

With the operationalisations from Section 3.2 and with the help of regression analysis, it is possible to test the hypotheses. In this section it is specified which the variables are, as well as the specifics of the regression model employed.

Table 3.1: Variables

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Polarity	16,661	2.064	2.017	0	0	3	15
Negativity	16,661	1.239	1.482	0	0	2	12
Positivity	16,661	0.826	1.111	0	0	1	10
Order	16,661	41.399	59.115	1	7	50	395
Spread	16,661	657.601	7,526.322	0	5	99	204,047
Followers	16,661	9,602.809	56,369.490	1	463	4,669	2,115,191

To test H1, this paper can be said to conduct a discrete time-series analysis based on the negative binomial regression model. This is because of the nature of the variables. The dependent variable—the variable to be explained—is polarity of sentiment (Polarity), measured using sentiment analysis. The actual variable is a count of positive and negative words included in each analysed tweet. The distribution of the variable can be seen in Figure 3.1.

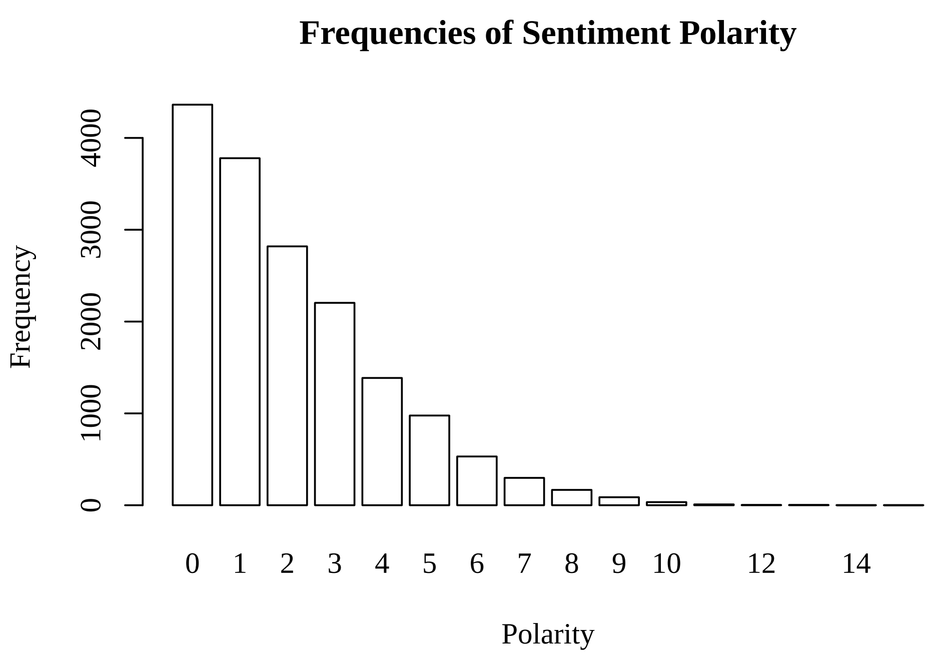

Figure 3.1: Dependent Variable Visualised

To get the best estimate of standard errors, which is crucial for correctly assessing the significance of regression results, a model with a count data dependent variable is best based on Poisson regression or negative binomial regression. Negative binomial regression is preferred if the dependent variable in the model suffers from over-dispersion (Cameron and Trivedi 1990, p. 355). Based on a statistical test for identifying over-dispersion, over-dispersion is present in the data set, which is why negative binomial regression is used rather than Poisson regression throughout the paper. The model also gets the characteristic of a discrete time series regression because of the nature of the independent variable, that is, the order of posting of tweets from the same account (see Körner and Wahlgren 2012, pp. 28–30,179–182). The same account, and most of the time the same individual, is observed several times across time. These points in time, however, are not regular or the same for different individuals since the variable is a result of individuals differing posting habits.

It is reasonable to assume that the extent to which individuals use a polarised language varies a lot based on their individual background and properties. This runs the risk of obscuring the relationship between interaction with conspiracy theories across time and polarity of sentiment. Individual differences might both conceal an in fact significant relationship, as well as, make it appear as if there is a significant relationship when in fact there is none. To remedy this problem the regression model uses the fixed effects approach (see Möhring 2012, pp. 7,8). This means that all the variance which is caused by individual differences is taken out leaving only variance across time. In practical terms, this is achieved through equipping the model with dummy-variables for each individual Twitter account in the data set.

In addition, to make sure that a relationship between polarity of sentiment and interaction with conspiracy theories is not driven by either negativity or positivity alone, two separate models are run with Positivity and Negativity—instead of Polarity—as the dependent variable. If there is a big difference between Negativity and positivity, the concept of polarity can be said to be put into question.

H2 and H3 can be described as interaction effects since they both state something about how the strength of the relationship between polarity of sentiment and order of tweets varies over some third variable. Testing for such effects is easily done by introducing a term in the regression model where the original independent variable is multiplied with the variable which it is thought interact with. Just like with H1, the test is made in three separate models, one with Polarity, one with Negativity, and one with Positivity as the dependent variable.

4 *Results*

4.1 Testing H1

> **Hypothesis 1 (H1):** *The more individuals interact with conspiracy theories, the more polarised their sentiment when addressing these same conspiracy theories.*

As was described in Section 3.3, H1 is tested using a bivariate negative binomial regression model with fixed effects on the level of the individual. The model tests for a relationship between the variables Polarity and Order, corresponding to the concepts of sentiment polarity and time ordering of tweets.

The results can be found in Table 4.1, model 1. The table shows that there is a highly significant positive relationship between Polarity and Order after differences on the level of the individual has been accounted for. This means that on average the next tweet of an account uses more negative or positive words than the tweet before. A higher value of Order is related to a higher value of Polarity. The finding is in accordance with H1.

The strength of the relationship is illustrated in Figure 4.1. According to the model, Polarity, as measured by the count of negative and positive words, goes up by about 0.2 per 100 tweets. Considering the small number of words in a tweet and the average of the Polarity variable (2.064), this is a noteworthy prediction. (It is worth keeping in mind that because the prediction is based on a fixed effects model the absolute values on the y-axis in Figure 4.1 should not be regarded; what is relevant is the relative changes over the length of the x-axis.)

To make sure that the relationship between Polarity and Order is not driven by the count of either positive or negative words alone, separate regression models are run with the alternative independent variables Positivity and Negativity. Both these models show a significant relationship suggesting that the measures can be aggregated and generalised to Polarity instead of either Negativity or Positivity. However, from Figure 4.2 it can be noted that the relationship is slightly stronger for Negativity than for Positivity, once again absolute values on the y-axis should not be regarded because of the fixed effects approach, only relative changes over the x-axis are of interest. The relationship between Negativity and Order also comes with a much higher significance than Positivity does, meaning that it is much more unlikely that the apparent relationship with Negativity is a product of chance than that of Positivity. This is evident from Table 4.1.

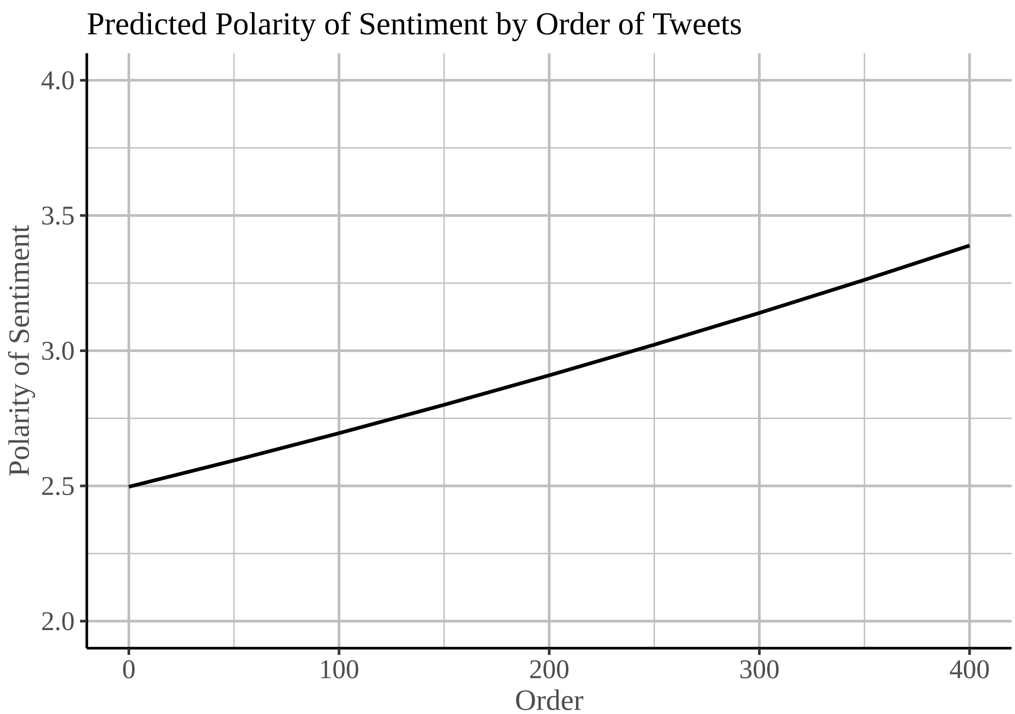

Figure 4.1: Prediction

Table 4.1: Bivariate Model

	Dependent variable:		
	Polarity	Negativity	Positivity
	negative binomial	*negative binomial*	*negative binomial*
	(1)	(2)	(3)
Order	0.001***	0.001***	0.001*
	(0.0002)	(0.0002)	(0.0003)
Observations	16,661	16,661	16,661
Log Likelihood	−29,128.370	−23,119.590	−19,001.170
θ	4.700*** (0.188)	4.142*** (0.216)	4.819*** (0.366)
Akaike Inf. Crit.	60,052.740	48,035.180	39,798.340
Note:			*p<0.05; **p<0.01; ***p<0.001 Fixed effects model

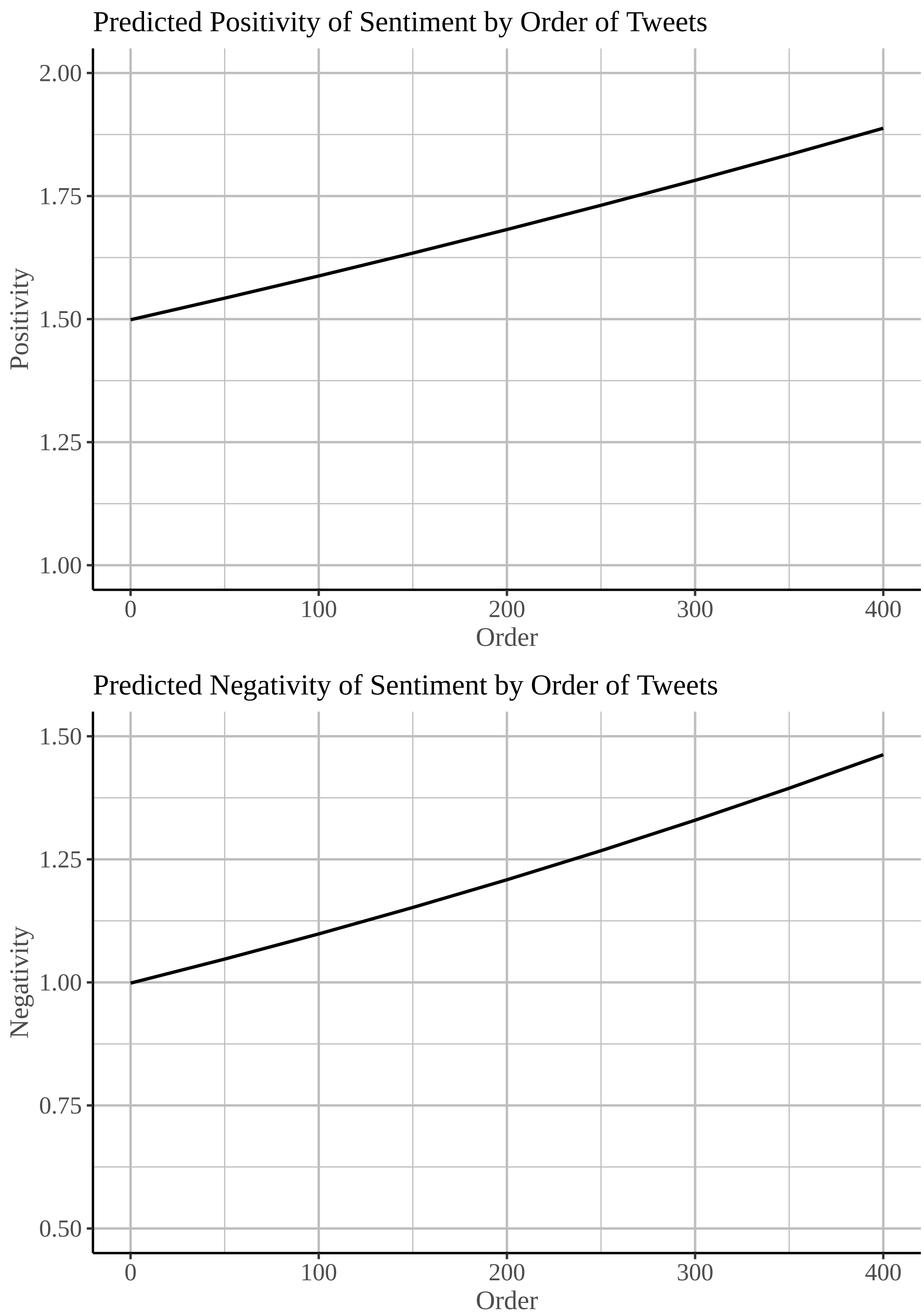

Figure 4.2: Prediction

4.2 Testing H2 and H3

> **Hypothesis 2 (H2):** *The more recognition individuals get for their interaction with conspiracy theories, the greater the effect in H1.*

> **Hypothesis 3 (H3):** *The more established a conspiracy theorist is online, the greater the effect in H1.*

To test H2 and H3 this paper again uses a negative binomial regression model with fixed effects on the level of the individual. The effects proposed by H2 and H3 are represented by interaction effects between the main independent variable Order and the two variables Recognition and Establishment. Just as before, besides the model with Polarity as the dependent variable, two separate models instead using Neagtivity and Positivity are also estimated. When the interaction terms are introduced the results are more diverse than in the bivariate model. These results are presented in Table 4.2. The basic relationship between Polarity and Order is still clear and strong and appear to not have been affected too much by the introduction of the new variables. This in itself is another sign that the relationship proposed by H1 is robust and general. The interaction effects themselves show no such robustness since none of them reach conventional levels of significance. This result is in violation with H2 and H3.

Although there is no significance—or at least no strong significance—for any of the interaction effects, they do seem to reveal a pattern of difference between Negativity and Positivity. That is, the direction of the interaction effect are different for Negativity and Positivity, something that could explain the very high p-values of the interaction effects in the polarity model. For Negativity and Positivity the p-values are lower and could be said to approach significance, at least in the case of Spread as a predictor of Negativity. The result suggests that a larger spread makes the relationship between Order and sentiment—in this case in the form of Negativity—stronger. This would have been in accordance with H2, only that the dependent variable has been changed from Polarity to Negativity. The strength of this interaction effect can be seen in Figure 4.3 by comparing the predictions of Negativity over Order for a lower value (close to the mean) and an arbitrarily chosen higher value of Spread. The shaded areas in the plot represent confidence intervals and show that there certainly is a trend in the model, there is however considerable overlap, meaning that there is no significant difference between the two predictions.

4.3 Summary

In summary, the findings appear to support some but not all of the hypothesised relationships. The relationship between Order, as measured by the order of tweets, and Polarity, as measured by the number of negative and positive words in tweets, is strong. The relationship also appears to exist both for Negativity and Positivity, thereby supporting the notion of polarity of sentiment as a concept. However, none of the interaction effects reach significance, although the model does come with an insignificant interaction in the hypothesised direction between Recognition and Order. All in all, H1 is supported but H2 and H3 are rejected, but there are still indications of a more complex reality. In Section 5 the implications of these results are discussed in more detail.

Table 4.2: Multivariate Model

	Dependent variable:		
	Polarity	Negativity	Positivity
	negative binomial	*negative binomial*	*negative binomial*
	(1)	(2)	(3)
Order	0.001^{***}	0.001^{**}	0.001^{**}
	(0.0002)	(0.0003)	(0.0003)
Followers	0.00001	0.00002	0.00001
	(0.00001)	(0.00002)	(0.00002)
Spread	0.00000	-0.00001^{*}	0.00002^{**}
	(0.00001)	(0.00001)	(0.00001)
Followers * Order	−0.00000	0.00000	−0.00000
	(0.00000)	(0.00000)	(0.00000)
Spread * Order	0.00000	0.00000^{+}	−0.00000
	(0.00000)	(0.00000)	(0.00000)
Observations	16,661	16,661	16,661
Log Likelihood	−29,126.750	−23,116.650	−18,996.650
θ	4.703^{***} (0.188)	4.159^{***} (0.217)	4.837^{***} (0.369)
Akaike Inf. Crit.	60,055.500	48,035.310	39,795.290

Note: Fixed effects model
+ p<0.1; * p<0.05; ** p<0.01; *** p<0.001

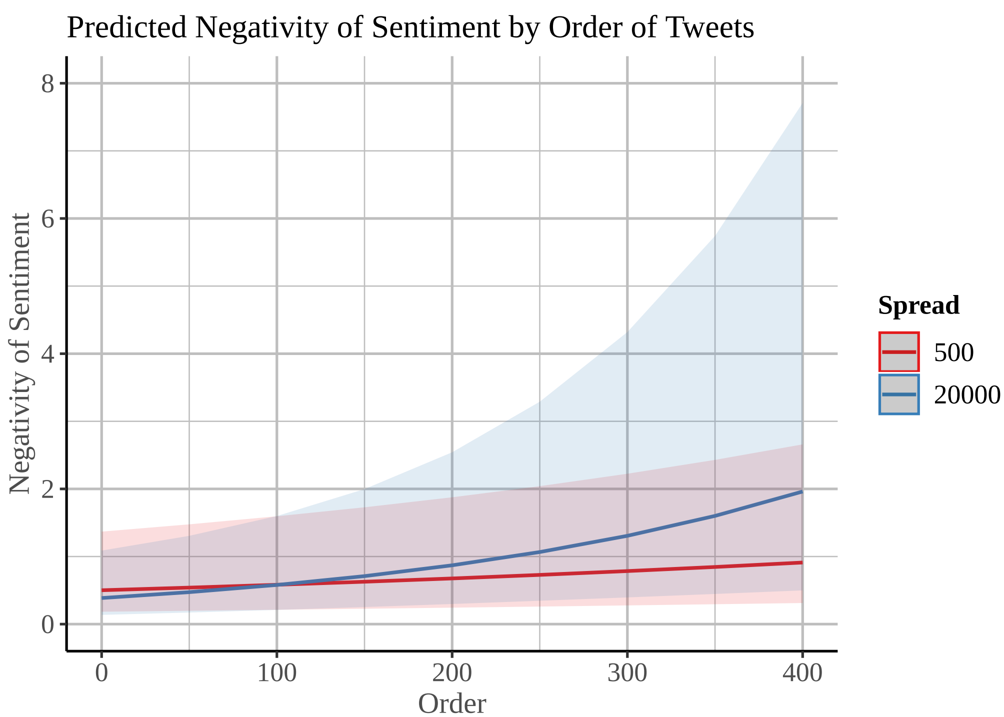

Figure 4.3: Prediction

5 *Conclusion*

Bringing the paper back to its theoretical foundation, the results are mixed. With the operationalisations specified in Section 3.2, there is evidence confirming a positive effect of attitude polarisation on the sentiment of conspiracy-theoretic communication online. That is, over time, as individuals interact with conspiracy theories, the language of their texts becomes more polarised, containing more negative, as well as, positive words. This is true at least when looking at conspiracy theories about George Soros and how they are communicated on Twitter. As is clear from the initial claim above, this paper argues that it is reasonable to generalise and make claims about conspiracy theories as a phenomenon. This is so, not the least since attitude polarisation in itself is a very general concept, thought to influence most human communication. There are no obvious reasons for why attitude polarisation would lead to sentiment polarisation for one conspiracy theory but not for another. Surely, however, there are nuances in the relationship which could be revealed by further research. It would, of course, also be good to see the findings of this paper be confirmed, for example by looking at other conspiracy theories or using alternative ways of operationalising theoretical concepts. As is stated in Section 3.2, many of the operationalisations used in this paper could have been improved if additional time and resources were available. It would strengthen the claims presented here considerably if they were reproduced using more sophisticated methods such as machine learning algorithms for identifying context bound sentiment—or even hand-coding. Data wise, it could be of interest to look not only at Twitter or to look more extensively at the timelines of users and thereby get a direct measurement of exposure instead of having to rely on users interaction as a proxy.

The question remaining after the initial finding that attitude polarisation appears to lead to sentiment polarisation is which of the several proposed possible mechanisms of attitude polarisation is behind the effect. Specifically, is the observed polarisation a result of exposure to conspiracy theories over time (biased assimilation), or is it rather a result of social dynamics (social establishment and recognition) in interaction with conspiracy theories? In the case of exposure and biased assimilation, that is, confirmation bias when considering evidence, communication about conspiracy theories would not directly cause polarisation. Instead, such communication would be a proxy for exposure, useful as a way of revealing the tendency but not a part of the causal chain and consequently not a potential tool for affecting the spread of conspiracy theory belief. In case polarisation is caused by social dynamics, communicating conspiracy theories does have a place in the causal chain.

In one way this paper presents a clear answer to whether or not social mechanisms are part of the explanation behind sentiment polarisation among conspiracy theorists, in another it might not. The simple answer is to say that social dynamics have nothing to do with online sentiment polarisation. There is no significance for social Recognition or Establishment and their effects in the models, using Polarity as the dependent variable, when there at the same time is strong correlational evidence supporting sentiment polarisation as hypothesised in H1.

However, it is questionable that social Recognition and Establishment—especially in their current operationalisations—properly capture the complexities of social networks and social status. Not the least since this paper only looks at Twitter, meaning that many other potential platforms for social interplay are disregarded, possibly skewing the view. There might also be other variables affecting the actual phenomenon of social establishment and recognition, even on Twitter, for example characteristics of users' Twitter-networks, like how active one's followers are or how closely they are inter-related with each other. When looking at Negativity and Positivity separately, instead of combined in the form of Polarity, such thinking can be argued to gain at some support. Although doing so does not question the general finding that the concept of polarity of sentiment develops as individuals interact with conspiracy theories, it does show that when talking about the concepts of social establishment and recognition, negative and positive sentiment might no longer be rightly generalised and aggregated into polarisation of sentiment. On top of this, it appears as though there actually might exist an interaction effect between Negativity and Recognition. This means that an individual who gets a lot of recognition for their interaction with conspiracy theories is quicker to use a more negative sentiment than someone who is not very extensively recognised. In this paper, this relationship does not quite reach conventional levels of significance, but if in fact there is such a relationship it suggests that social mechanism, such as recognition and establishment, do have something to do with sentiment. It is however outside the scope of the theorising and hypothesising of this paper to explain this deviance and possible specificity of negative sentiment as compared to positive sentiment. Further endeavours to understand this dynamic would thus be a promising area for further studies.

The substantial finding of this paper is, in summary, that communication about conspiracy theories somehow relating to George Soros is polarised in its sentiment as those who communicate are exposed to information about the theories. This is explained by the general tendency of attitude polarisation and likely specifically by the process of biased assimilation. Although there is no support for the hypothesis that the relationship between sentiment polarisation and attitude polarisation is caused by the concepts of social recognition or establishment, there are indications that such social dynamics might exist when looking only at escalating negative sentiment.

In a second step, no matter potential social dimensions, this all suggests that exposure to conspiracy theories have very real implications for the sentiment of online public discourse, making it more polarised. What this, in turn, means for political and democratic values is not clear from the present study but it can be said to reinforce worries about polarisation, especially in online communities, and about what polarisation might do to our democratic institutions. As is shown by previous research, conspiracy theory believers are sceptical of public institutions, less inclined to participate politically, more accepting towards political violence, and immune to information debunking their conspiracy theories. From this paper it has been established that as individuals interact with conspiracy theoretic information they also facilitate a more polarised sentiment in online discourse. If the polarisation of conspiracy theory related sentiment is infused with the aforementioned tendencies, they might run the risk of being further exacerbated and diffused. Such processes then, in effect, could constitute serious issues for democracy. However, for this to be the case it needs to outweigh the potential utility of conspiracy theories as channels of criticism of societal norms and structures, something that will have to be developed on in further research.

Bibliography

Abalakina-Paap, Marina; Stephen, Walter G.; Craig, Traci, and Gregory, Larry W. 1999. "Beliefs in Conspiracies". *Political Psychology* 20 (3): 637–647.

Bartlett, Jamie and Carl, Miller. 2010. *The Power of Unreason: Conspiracy Theories, Extremism and Counter-Terrorism.* London: Demos.

Bessi, Alessandro; Coletto, Mauro; Davidescu, Alexandru; Scala, Antonio; Calderelli, Guido, and Quattrociocchi, Walter. 2015a. "Science vs Conspiracy: Collective Narratives in the Age of Misinformation". *PLOS ONE* (): 1–18.

Bessi, Alessandro; Petroni, Fabio; Del Vicario, Michela; Zollo, Fabiana; Anagnostopoulos, Aris; Scala, Antonio; Caldarelli, Guido, and Quattrociocchi, Walter. 2015b. "Viral Misinformation: The Role of Homophily and Polarization". doi:`10.1145/2740908.2745939`.

Bessi, Alessandro; Zollo, Fabiano; Del Vicario, Michela; Scala, Antonio; Calderelli, Guido, and Quattrociocchi, Walter. 2015c. "Trend of Narratives in the Age of Misinformation". *PLOS ONE* (): 1–16.

Cameron, A. Colin and Trivedi, Pavin K. 1990. "Regression-Based Tests for Overdispersion in the Poisson Model". *Journal of Economiterics* 46:347–364.

Cichocka, Aleksandra; Marchlewska, Marta, and De Zavala, Agnieszka Golec. 2016. "Does Self-Love or Self-Hate Predict Conspiracy Beliefs? Narcissism Self-Esteem, and the Endorsement of Conspiracy Theories". *Social Psychological and Personality Science* 7 (2): 157–166.

Claassen, Ryan L. and Ensley, Michael J. 2016. "Motivated Reasoning and Yard-Sign-Stealing Partisans: Mine is a Likable Rouge, Yours is a Degenerate Criminal". *Political Behaviour* 38:317–335.

Dagnall, Neil; Denovan, Andrew; Drinkwater, Kenneth; Parker, Andrew, and Clough, Peter J. 2017. "Urban Legends and Paranormal Beliefs: The Role of Reality Testing and Schizotypy". *Frontiers in Psychology* 8 (942).

Dandekar, Pranav; Goel, Ashish, and Lee, David T. 2013. "Biased assimilation, homphily, and the dynamics of polarization". *Procedings of the National Academy of Sciences of the United States of American* 110 (15): 5791–5796.

Douglas, Karen M.; Sutton, Robbie M.; Callan, Mitchell J.; Dawtry, Rael J., and Harvey, Annelie J. 2016. "Someone is pulling the strings: hypersensitive agency detection and belief in conspiracy theories". *Thinking and Reasoning* 22 (1): 57–77.

Douglas, Karen M.; Sutton, Robbie M., and Cichocka, Aleksandra. 2017. "The Psychology of Conspiracy Theories". *Current Directions in Psychological Science* 26 (6): 538–542.

Douglas, Karen M.; Uscinski, Joseph E.; Sutton, Robbie M.; Cichocka, Aleksandra; Nefes, Turkay; And, Chee Slang, and Deravi, Farzin. 2019. "Understanding Conspiracy Theories". *Advances in Political Psychology* 40 (1): 3–35.

Edelson, Jack; Alduncin, Alexander; Krewson, Christopher; Sieja, James A., and Uscinski, Joseph. 2017. "The Effect of Conspiratorial Thinking and Motivated Reasoning in Belief in Election Fraud". *Political Research Quarterly* 70 (4): 933–946.

Einstein, Katherine Levine and Glick, David M. 2015. "Do I Think BLS Data are BS?: The Consequences of Conspiracy Theories". *Political Behavior* 37 (3): 679–701.

— . 2013. "Scandals, Conspiracies and the Vicious Cycle of Cynicism". Working paper prepared for the 2013 APSA meetings.

Franks, Bradley; Bangerter, Adrian, and Bauer, Martin W. 2013. "Conspiracy theories as quasi-religious mentality: an integrated account from cognitive science, social representations theory, and frame theory". *Frontiers in Psychoogy* 4 (424): 1–22.

Freeman, Daniel and Bentall, Richard P. 2017. "The concomitants of conspiracy concerns". *Social Psychiatry and Psychiatric Epidemiology* 52 (5): 595–604.

Goertzel, Ted. 1994. "Belief in Conspiracy Theories". *Political Psychology* 15 (4): 731–742.

Grant, Lenny; Hausman, Bernice L.; Cashion, Margaret; Lucchesi, Nicholas; Patel, Kelsey, and Roberts, Jonathan. 2015. "Vaccination Persuasion Online: A Qualitative Study of Two Provaccine and Two Vaccine-sceptical Websites". *Journal of Medical Internet Research* 19 (5).

Grewal, David Singh. 2016. "Conspiracy Theories in a Networked World". *Critical Review* 28 (1): 24–43.

Imhoff, Roland and Burder, Martin. 2014. "Speaking (Un-)Truth to Power: Conspiracy Mentality as a Generalised Political Attitude". *European Journal of Personality* 28:25–43.

Imhoff, Roland and Lamberty, Pia Karoline. 2017. "Too special to be duped: Need for uniqueness motivates conspiracy beliefs". *European Journal of Social Psychology* 47:724–734.

Jerit, Jennifer and Barabas, Jason. 2012. "Perceptual Bias and the Information Environment". *The Journal of Politics* 74 (3): 672–684.

Jolley, Daniel and Douglas, Karen M. 2014. "Thesocial consequences of conspiracism: Exposure to conspiracy theories decreases intentions to engage in politics and to reduce one's carbon footprint". *British Journal of Psychology* 105 (1): 35–56.

Jost, John T.; Glaser, Jack; Kruglanski, Arie W., and Sulloway, Frank J. 2003. "Political Conservatism as Motivated Social Cognition". *Psychological Bulletin* 129 (3): 339–375.

Körner, Svante and Wahlgren, Lars. 2012. *Praktiskt Statistik*. 4th ed. Lund: Studentlitteratur.

Lantian, Anthony; Muller, Dominique; Nurra, Cécile; Klein, Olivier; Berjot, Sophie, and Pantazi, Myrto. 2018. "Stigmatized beliefs: Conspiracy theories, anticipated negative evaluation of the self, and fear of social exclusion". *European Journal of Social Psychology* 48:939–954.

Lee, Benjamin J. 2017. "'It's not paranoia when they are really out to get you': the role of conspiracy theories in the context of heightened security". *Behavioral Sciences of Terrorism and Political Aggression* 9 (1): 4–20.

Leman, Patrick J. and Cinnirella, Marco. 2013. "Beliefs in conspiracy theories and the need for cognitive closure". *Frontiers in Psychology* 4 (378).

Lobato, Emilio; Mendoza, Jorge; Sims, Valerie, and Chin, Matthew. 2014. "Examining the Relationship Between Conspiracy Theories, Paranormal Beliefs and Pseudoscience Acceptance Among a University Population". *Applied Cognitive Psychology* 28:617–625.

Lord, Charles G.; Ross, Lee, and Lepper, Mark R. 1979. "Biased Assimilation and Attitude Polarization: The Effects of Prior Theories on Subsequent Considered Evidence". *Journal of Personality and Social Psychology* 37 (11): 2098–2109.

McHoskey, John W. 1995. "Case Closed? On the John F. Kennedy Assassination: Biased Assimilation of Evidence and Attitude Polarization". *Basic and Applied Social Psychology* 17 (3): 395–409.

Mikuskova, Eva Ballova. 2017. "Conspiracy Beliefs of Future Teachers". *Current Psychology* 37:692–701.

Miller, Shane. 2002. "Conspiracy Theories: Public Arguments as Coded Social Critiques: A Rhetorical Analysis of the TWA Flight 800 Conspiracy Theories". *Argumentation and Advocacy* 39:40–56.

Möhring, Katja. 2012. "The fixed effect as an alternative to multilevel analysis for cross-national analyses". *GK SOCLIFE* ().

Moore, Alfred. 2016. "Conspiracy and Conspiracy Theories in Democratic Politics". *Critical Review* 28 (1): 1–23.

Myers, David G. and Lamm, Helmut. 1976. "The Group Polarization Phenomenon". *Psychological Bulletin* 83 (4): 602–627.

Nefes, Türkay Salim. 2013. "Political parties' perceptions and uses of and-Semitic conspiracy theories in Turkey". *The Sociological Review* 61:247–264.

Oliver, J. Eric and Wood, Thomas J. 2014. "Conspiracy Theories and the Paraniod Style(s) of Mass Opinion". *American Journal of Political Science* 58 (4): 952–966.

Raab, Marius H.; Ortlieb, Stefan A.; Auer, Nikolas; Guthmann, Klara, and Carbon, Claus-Christian. 2013. "Thirty shades of truth: conspiracy theories as stories of individuation, not of pathological delusion". *Frontiers in Psychology* 4 (406): 1–9.

Sapountzis, Antonis and Condor, Susan. 2013. "Conspiracy Accounts as Intergroup Theories: Challenging Dominant Understandings of Social Power and Political Legitimacy". *Political Psychology* 34 (5): 731–752.

Simmons, William Paul and Parsons, Sharon. 2017. "Beliefs in Conspiracy Theories Among African Americans: A Comparison of Elites and Masses". *Social Science Quarterly* 87 (3): 582–598.

Smallpage, Steven M.; Enders, Adam M., and Uscinski, Joseph E. 2017. “The partisan contours of conspiracy theory beliefs”. *Research and Politics* (): 1–7.

Sunstein, Cass R. 2002. “The Law of Group Polarization”. *The Journal of Political Philosophy* 10 (2): 175–195.

Thorson, Emily. 2016. “Belief Echoes: The Persistent Effects of Corrected Misinformation”. *Political Communication* 33:460–480.

Van Prooijen, Jan-Willem. 2017. “Why Education Predicts Decreased Belief in Conspiracy Theories”. *Applied Cognitive Psychology* 31:50–58.

Van Prooijen, Jan-Willem and Douglas, Karen M. 2017. “Conspiracy theories as a part of history: The Role of societal crisis situations”. *Memory Studies* 10 (3): 323–333.

Van Prooijen, Jan-Willem; Douglas, Karen M., and De Inocencio, Clara. 2018. “Connecting the dots: Illusory pattern perception predicts belief in conspiracies and the supernatural”. *European Journal of Social Psychology* 48:320–335.

Van Prooijen, Jan-Willem and Jostmann, Nils B. 2013. “Belief in conspiracy theories: The influence of uncertainty and preceived morality”. *European Journal of Social Psychology* 43 (1): 109–115.

Van Prooijen, Jan-Willem; Krouwel, André P.M., and Pollet, Thomas V. 2015. “Political Extremism Predicts Belief in Conspiracy Theories”. *Social Psychological and Personality Science* 6 (5): 570–578.

Vitriol, Joseph A. and Marsh, Jessecae K. 2018. “The illusion of explanatory depth and endorsement of conspiracy theory belief”. *European Journal of Social Psychology* 48:955–969.

Whitfield, Stephen J. 2018. “The Persistence of the *Protocols*”. *Society* 55:417–421.

Wood, Michael J. and Douglas, Karen M. 2015. “What about building 7?” A social psychological study of online discussion of 9/11 conspiracy theories”. *Frontiers in Psychology* 4 (409): 1–16.

Young, Lori and Soroka, Stuart. 2012. “Affective News: The Automated Coding of Sentiment in Political Texts”. *Political Communication* 29 (2): 205–231.

Zollo, Fabiana; Novak, Petra Kralj; Del Vicario, Michela; Bessi, Alessandro; Mozetic, Igor; Scala, Antonio; Calderelli, Guido, and Quattrociocchi, Walter. 2015. “Emotional Dynamics in the Age of Misinformation”. *PLOS ONE* (): 1–22.