The Effect of Knowledge Claims on the Diffusion of Narratives: Social Media Messaging of European Parliarmentarians on Twitter

Kohn, Philipp

Universiteit Leiden
Governance and Global Affairs

UNIVERSITEIT LEIDEN

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Author:
Philipp Kohn
p.kohn@umail.leidenuniv.nl
ID: s2693240

Supervisor:
Prof. Dr. Johan Christensen

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I would like to thank my parents for their love and patience. I would not be where I am today without their hard work. Mama, get well soon.

Abstract

This thesis aims to explain the effect of knowledge claims on the diffusion of narratives uttered by European Parliamentarians (EP) in social media messaging. Utilising the narrative policy framework (Jones & McBeth, 2010), a theoretical framework is constructed to conceptualise narrative persuasiveness and make sense of the strategic rhetoric of political actors. To provide insights into the role of knowledge claims in narratives, the theoretical framework was enriched by Boswell et al.'s (2011) conceptualisation of this relationship. To understand how tweets behave in general on Twitter, this thesis draws from Margetts, John, Hale, & Yasseri (2016) and identifies a power-law distribution within the data. This challenge will be approached by log-transforming the data (see Raban & Rabin, 2009).

Around 500,000 EP tweets collected by van Vliet, Törnberg, & Uitermark (2020) between September 2017 and April 2019 are considered for the explanatory linear models presented in this thesis. The dependent variable is retweet count, and the independent variable is knowledge claims. Each observation is assigned a knowledge claim dummy variable according to the results of a keyword search. Keywords were selected deductively based on Carpenter's (2010) definition of 'technical reputation' (see Busuioc & Rimkutė, 2020). Subsequently, the keyword search will be validated by applying two 'keywords in context' algorithms to measure hashtag frequencies and infer topics referred to across the categories 'knowledge claim' and 'non-knowledge claim' (see Benoit et al., 2018).

The results show that knowledge claims affect retweet count negatively when a tweet reacts on another tweet, i.e. retweet, and positively in cases where tweets initiate the diffusion process, i.e. original tweet. This thesis argues that this effect can be explained by Jasanoff (2004), who formulates the *co-production of science* phenomenon. Furthermore, this thesis shows that log-transformation is a great tool to approach the non-normal distribution of Twitter data and discusses the challenges and opportunities of big data in social science research.

Keywords: Knowledge claims, policy narratives, social media messaging, persuasion, diffusion.

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Chapter 1

Introduction

This thesis asks the question of how knowledge claims affect the diffusion of narratives. This question is directed toward European Parliamentarian (EP) narratives and aims to understand how EPs utilise knowledge claims to engage with the public through social media messaging on Twitter. Accordingly, this thesis follows a growing body of literature that examines the possibility of utilising social media data for social science research (see Gupta, Ripberger, & Wehde, 2018; McBeth, Shanahan, Arrandale Anderson, & Rose, 2012). The puzzle this thesis addresses is twofold.

Firstly, the following research question shall be answered:

> *"How do knowledge claims affect the diffusion of English language tweets authored by European Parliamentarians between 2017 and 2019?"*

In the context of the growing diversification of science and data, this question is relevant to both constituencies, who are subjected to knowledge claims as a form of strategic rhetoric, and policymakers, who become increasingly reliant on evidence to approach uncertainties of increasingly complex policy problems (Jasanoff, 2004). The use of knowledge to effectively communicate policy narratives to constituencies, on the one hand, and the necessity of evidence in policymaking to deal with uncertainty, on the other, create a tension worth investigating. This thesis aims to examine how this tension affects the political communication of EPs with their audience on Twitter.

Secondly, the research question will be answered by utilising Twitter data and linear regression models. While applying social media data for social science research provides excellent research opportunities, it also poses several challenges. Opportunities may include the cheap and fast availability of large amounts of data compared to traditional sources (Lukoianova & Rubin, 2014). Challenges include the delineation of the population, which potentially hinders the replication of research and poses a threat to the representability of the sample population (van Vliet et al., 2020). Furthermore, heavily skewed data makes it impossible for linear models to measure statistically robust effects on untransformed data (Raban & Rabin, 2009). By scrutinising social media data to answer the research question empirically, this thesis aims to explore the use of this new data source for social science research.

A query of the keyword combination 'Twitter' and 'politics' retrieves 640 articles written between 2018 and 2019 from the web of knowledge database, 279 of which have been published in this period (van Vliet et al., 2020, p. 2). This makes for roughly one article every three days. Enjolras (2014) points out that politicians' use of social media platforms as means of political communication is expected to result in new ways of communication between politicians and their constituents. Social media platforms can provide a more dialogical form of communication in which politicians speak directly to their supporters (Enjolras, 2014).

In combination with the increasing use of social media platforms on the part of political actors, academic scrutiny of political activity on social media platforms becomes more relevant. This thesis attempts to provide research to this growing body of literature and explore how parliamentarians might utilise references to evidence and expert knowledge, such as statistics or research, to boost the persuasiveness of their claims and generate greater support for their narratives.

The academic relevance of this research is threefold. Firstly, it provides an additional perspective to the study of knowledge claims in the contemporary setting of social media messaging. It connects research regarding knowledge claims in policy narratives (see Boswell, 2008) with research about the mobilisation of individuals on Twitter (see Cha, Haddadi, Benevenuto, & Gummadi, 2010; Enjolras, 2014; Margetts et al., 2016). Therefore, advancing the research on the study of knowledge claims. Secondly, this thesis aims to explore the use of Twitter data more generally. As more and more political actors use platforms like Twitter to engage with constituencies, it becomes more and more relevant to researchers concerned with political behaviour to scrutinise this new way of communication. Additionally, as van Vliet et al. (2020) point out, data on political behaviour on Twitter is plentiful but challenging to work with. Twitter data follows the challenges of big data. Lukoianova & Rubin (2014) point out that volume, velocity, and variety of big data produce challenges of veracity. Veracity refers to biases, ambiguities, and inaccuracies found in data (Lukoianova & Rubin, 2014). Scholars like van Vliet et al. (2020) attempt to provide solutions to challenges related to veracity, such as the population's delineation, sampling, and validation. This research utilises the solution presented by van Vliet et al. (2020) and explores its applicability to the positivist research approach toward the study of narratives. Lastly, a central critique on the study of narratives, brought forth by Sabatier (2007), is the quantifiability of this rather qualitative subject. Following Jones & McBeth (2010), this thesis attempts to challenge this problem and explore the use of social media data in connection with quantifiable hypotheses to provide a positivist approach to the study of narratives and satisfy Sabatier's (2007) critique McBeth et al. (2012).

According to Boswell et al. (2011), a number of scholars have suggested that political debates increasingly centre on the deployment of competing knowledge claims. With increasing knowledgeability of the world and the government sector

(Boswell et al., 2011, p. 7), individuals get continuously exposed to academic knowledge, technology, and data. This leads to growing expectance of evidence-based policymaking. In a world where it is possible to look up the entire knowledge of humanity at the click of a button and where one can monitor pulse and sleep through smartwatches at any time, awareness of the use and availability of data increases among individuals. This awareness potentially creates expectations for leaders to be informed about their decisions and in control of the situation. At the same time, the growing complexity of some policy areas pressures policymakers to deal with increasing risks stemming from uncertainty Boswell et al. (2011). From a societal perspective, it is, therefore, relevant to understand how political actors engage with their constituencies regarding the use of knowledge claims in political communication. While the demand for evidence-based policymaking on the part of the public generally grows, actors may utilise this demand to engage in competition for validity (Boswell et al., 2011). The competitive use of knowledge claims often produces several opposing and contradicting knowledge claims. Therefore, societies have become increasingly sceptical of the credibility of competing knowledge claims (Boswell et al., 2011). In addition, the politicisation of science and expert knowledge may also have adverse effects on the production of science. Politicians could cherry-pick the evidence that fits best their purpose, which potentially leads to many studies gathering dust on bookshelves, not getting paid any attention, or not being financed in the first place as they have no apparent use case for policymakers.

With the growing availability of data and the diversification of science (see Jasanoff, 2004), it will become increasingly crucial for constituencies to be aware of the competitive use of evidence on the political stage and tell apart information from competition. A phenomenon coined by Jasanoff (2004) as the 'co-production of science and policy.'

Other scholars believe that the rise of knowledge claims in policy debates is linked to the decline of conventional ideological politics (see Fischer 1990; Davies et al. 1999. Cited after Boswell et al., 2011). Policy debates become more focused on technological concerns rather than normative value hierarchies. Furthermore, as the welfare state increases in complexity, ever more sophisticated tools of control and guidance become necessary. As the implementation of such tools must be supported by study, more technocratic debates find their way into the policymaking process (see Luhmann 1991. Cited after Boswell et al., 2011).

To extract meaningful insight about the use of knowledge claims in parliamentarian tweets, this thesis applies concepts relating to persuasiveness as put forth by the Narrative Policy Framework (NPF) constructed by Jones & McBeth (2010). An NPF guided conceptualisation will prove helpful in making sense of political communication and provide fundamental concepts to draw from when discussing the role of knowledge claims in parliamentarian tweets. Furthermore, this thesis will use the NPF's positivist approach and formulate falsifiable hypotheses and attempt to construct robust linear models from the learnings provided by Jones & McBeth (2010). Combining the NPF with a meaningful conceptualisation of knowledge claims in the context of narratives provides the basis of the empirical section below.

The paper will first conceptualise central terms and provide a theoretical context to interpret the findings. Additionally, the theory section will present an operationalisation of the concepts described in this thesis. The theory section will conclude in formulating hypotheses. The method section will first discuss the data set at hand and construct a data subset from the TPD. This will be done to reduce variability in the data to provide focus to the research. The paper will then continue to present three linear regression models, which are then deployed and scrutinised in the results section. Subsequently, the results of the linear regression models shall be discussed and put in the theoretical context. The paper then offers concluding remarks and provides ideas for future research, and critically evaluate the findings.

Chapter 2

Theoretical Framework

The following section will elaborate on the theoretical framework applied in this thesis and discuss the role of knowledge claims in policy narratives. Firstly, the narrative policy framework (NPF) shall be introduced (Jones & McBeth, 2010; Shanahan, Jones, & McBeth, 2018). This will provide a theoretical framework of how political actors communicate and enable the construction of a conceptualisation suitable for positivist research. Secondly, to provide a clear focus on the use of knowledge claims in political communication, this thesis will make use of Boswell et al.'s (2011) conceptualisation of 'knowledge claims' and their use by political actors. Subsequently, this thesis establishes a connection between the narrative concept and the knowledge claim concept. This thesis then adds a conceptualisation of the term 'diffusion' and puts it in the context of political communication in social media messaging. This will be necessary to provide a concise understanding of the effect of knowledge claims on the persuasiveness of narratives in social media messaging. After providing a theoretical foundation, three hypotheses about the diffusion of narratives on the social media platform Twitter will be formulated.

2.1 Policy Narratives

Unlike other concepts of the role narratives play in policymaking (Maarten, 1993; Roe, 1994; e.g., Stone, 1988), the NPF (see Jones & McBeth, 2010) — delivers a positivist approach and provides testable hypotheses. This is by no means to say that the NPF would be the only positivist approach to the study of narratives. However, after reviewing the secondary literature, it appears that the NPF is one of the most promising frameworks in this area. Scholars have applied the NPF in several policy areas, such as US nuclear energy policy (Gupta et al., 2018), narratives in hydraulic manufacturing in New York (Heikkila, Weible, & Pierce, 2014), or to provide a new perspective to the 'Arab Spring' (O'Bryan, Dunlop, & Radaelli, 2014). A large body of literature is, therefore, available to draw from when formulating a theoretical framework. Furthermore, it appears that the NPF has been subject to a lot of scientific attention and scrutiny over the last years, which provides confidence about its application as a positivist theoretical framework.

As Jones & McBeth (2010) point out, post-positivists often critique that narratives are not quantifiable as they are relative and thus immune to generalizability. To solve this problem and establish a generalisable context, Jones & McBeth (2010, p. 341) suggest that positivist research of narratives must be anchored in generalisable content. In this thesis' case, and as suggested by Jones & McBeth (2010), political communication will be viewed in the context of parliamentarian affiliation to party families according to the CHES (Polk et al., 2017). This limits variability to a sufficient extent for meaningful positivist research (Jones & McBeth, 2010).

It should be noted that this thesis will approach the term 'narrative' from a general perspective of political communication. This goes against Jones & McBeth (2010) definition of the term. The conceptualisation of what constitutes a narrative, according to Jones & McBeth (2010), is plot-driven and centres around characters and a story. For Jones & McBeth (2010), the narratives revolve around the story of a policy issue and a policy solution, or 'moral of the story,' and provides characters like problem causers, problem victims, and solution providers. Solution providers are referred to as 'heros' and defined as those that act toward realising or opposing a policy solution (Shanahan, Jones, & McBeth, 2011, p. 12). Problem causers are 'villains' and inflicts damage and harm upon the victim (Shanahan et al., 2011, p. 12). In some cases, villains also actively oppose the aims of the hero (Shanahan et al., 2011, p. 12). Lastly, the 'victims' are those that are negatively affected by an action or lack of action (Shanahan et al., 2011, p. 12). Additionally, Shanahan et al. (2011) provide six categories of plots that narratives typically fall into. For example, the 'story of decline' refers to narratives that describe how things once were good and now are bad, or the 'story of helplessness and control,' where the narrator describes how the current situation is traditionally accepted, even though it is bad, but can be changed nonetheless (Shanahan et al., 2011). According to Jones & McBeth (2010), a narrative is required to provide a policy solution to the issues described in the plot — a 'moral of the story.' However, Shanahan et al. (2011) point out that the NPF can and should be amended toward the specific requirements of the research at hand. Therefore, this thesis will provide a more general conceptualisation of narratives to comply with the requirements of the method and data discussed below. Coding for the identifiers described by Shanahan et al. (2011) to distinguish between narratives and non-narrative is expected to exceed its advantages as this would complicate the theoretical framework and restrict data selection. Twitter limits tweets to 280 characters. It is unlikely to identify a sufficient amount of messages in the dataset that fulfil the requirements of Jones & McBeth (2010) and show the use of knowledge claims. Furthermore, manually coding nearly 600.000 tweets is impossible considering the resources of this research.

Therefore, it will not be necessary to distinguish between policy narratives and other forms of political communication. Narratives are seen as a specific form of political communication, namely strategic political communication, with the aim to increase persuasiveness and diffuse a political message. The study of persuasion and strategic rhetoric are central subjects in both areas, policy narratives and political communication (Charteris-Black, 2011; see Jones & McBeth, 2010; Shanahan et al., 2018). Thus, this thesis will utilise literature on political communication to produce a broader perspective on narratives in the political context.

2.2 Persuasiveness

The following section discusses Jones & McBeth (2010) four hypotheses about the persuasiveness of policy narratives on the micro-level and put it in the context of Boswell et al. (2011) understanding of the term 'policy narrative.' The term 'persuasiveness' will further be set in the context of political communication literature. Additionally, the following paragraphs will introduce an understanding of the diffusion of narratives in social media messaging and attempt to shed light on the relationship between persuasiveness and diffusion.

Jones & McBeth (2010, p. 343) understand persuasiveness as the degree to which a narrative can change an individual's attitudes toward a policy issue. Jones & McBeth (2010) argue that *canonicity and breach, narrative transportation, congruence and incongruence,* and *narrator trust* are independent variables that positively affect the dependent variable persuasiveness. The following paragraphs will clarify each aspect but do not aim to be a thorough explanation of what makes a narrative persuasive. Beyond these categories, there are additional factors like rational interests that will influence the appeal of a narrative to a particular set of individuals (Boswell et al., 2011).

Congruence describes how well an individual can relate to a narrative based on its alignment with their life experience. Mattila (2000) points out that information presented in narrative form is better suited for processing by individuals as it is similarly structured to life experience. According to Jones & McBeth (2010), a narrative's persuasiveness is relative to its alignment to an individuals belief system. This circumstance lets individuals understand certain facets of a policy narrative more easily than others by functioning as a shortcut. The individual will be able to gauge congruence or incongruence more quickly. While congruence is preferred and, thus, more persuasive, incongruence is actively rejected (Jones & McBeth, 2010).

Furthermore, as communities share a common language and belief system, it is expected that the diffusion of a narrative has a positive effect on the congruence of that narrative. Assuming that an individual shares the narrative with the people of the community they belong to, it is reasonable to suspect that they will do so in a language that the community is used to. The narrative will be presented in a familiar context which increases congruence.

Canonicity, also called normalcy (Bruner, 1991; Herman, 2003, p. 179; 2004, p. 91), is seen as a situation of balance. In this situation, the world moves along as expected, and there is little reason to change it (Jones & McBeth, 2010). Breach interrupts this balance and breaks expectations, norms, and banality (Jones & McBeth, 2010). A narrative's persuasiveness is subjected to the extent of breach (Herman, 2003, 2004). This is to say that narratives that are more disruptive of the status quo are more persuasive. With increasing diffusion, a narrative's ability to challenge the status quo may be perceived to be high, as its importance or impact appears to be increased relative to other narratives with a lesser degree of diffusion.

The term *narrator trust* summarises an individuals perception of the trustworthiness, accuracy and objectivity, expert status, likability, and ideology of the narrative uttering actor. According to Jones & McBeth (2010), narrator trust influences an individual's willingness to accept a narrative: "the plausibility of a story is conditioned by the extent to which individuals trust the source of the narrative (Hovland & Weiss, 1951; Olson, 2003)" (Jones & McBeth, 2010).

When parliamentarian narratives get diffused by an individual, they will provide the actor with access to a larger community. These people then view the narrative filtered through the individual. If the individual shares the narrative with, for example, family members or friends, then the narrative is affected by the individual's relationship with the people they share it with, as the narrative is then viewed in the individual's context. Assuming that family members and friends trust each other, individuals may transpose the trust they receive from their communities onto the narrative. Therefore, narrator trust increases when individuals view political content in the context of trusted people, such as friends and family members, but also celebrities or organisations.

As described by Jones & McBeth (2010), *transportation* refers to a narrative's capability to make the individual "involved with its protagonists" (Green & Brock, 2005). Transportation determines to what extent an individual gets lost inside the narrative, changes, and returns (Jones & McBeth, 2010). Contrary to Jones & McBeth (2010), this thesis sees transportation as the outcome of persuasion. Transportation is not something that increases persuasiveness but something that is increased by persuasiveness. To make this point, this paper refers to Charteris-Black's (2011) understanding of persuasion on the individual level. According to Charteris-Black (2011, p. 14), persuasion is the outcome of strategic rhetoric, i.e. narratives, which causes a change in the individual's opinion toward what the actor intended. In other words, the individual is persuaded or transported when he or she experiences a change in opinion toward what was intended by the actor (Charteris-Black, 2011). Therefore, Charteris-Black's (2011) understanding of persuasion shows many similarities to Jones et al.'s (2010) conceptualisation of transportation. Both concepts refer to the ability of a narrative to draw an individual in, change them in some way, and release them changed. Therefore, this thesis will consider transportation as the outcome of persuasiveness. On the individual level, transportation is the intermediate step toward the diffusion of a narrative within a community.

2.3 Diffusion

In his book 'The Diffusion of Innovation,' Rogers (1962) has formally conceptualised diffusion and its meaning to the adoption of new ideas and social behaviour. Following Rogers' (1962) formal interpretation, scholars from multiple disciplines have re-interpreted and amended the concept in over four thousand scientific pieces (Greendale et al., 2005). Thus, it is no surprise that it is not possible to determine one universal interpretation of the term. Additionally, human behaviour is not rational and challenging to predict. How something diffuses among a population of people is depended on the thing itself. Thus, a theory of diffusion applied by one scholar does not apply to the use case of another. It is, therefore, the aim of this section to determine what diffusion of a narrative means for a population of individuals in a political context.

This thesis refers to *diffusion* as the extent to which a narrative has spread among members of a population. Put differently, *diffusion* is the degree to which a narrative has transported the individuals within a population. As described above, diffusion is related to the concept of transportation. Transportation describes the process of drawing an individual in and returning them changed through the use of rhetoric tools. In the following, diffusion is considered as an additional concept in understanding how political communication behaves.

Granovetter and Soong's (1983) model is based on Schelling's (2006) threshold of collective mobilisation and is based on the assumption that individuals will choose to participate in an activity based on how many other individuals are already involved in the activity. The model is concerned only with binary decisions, such as joining a riot or not. Granovetter & Soong (1983) point out that an individuals' wish to join a riot depends in part on how many people are already involved. It is riskier to join early on when few others have, as the odds of being apprehended are higher. According to Granovetter & Soong (1983), some individuals are more risk-seeking while others are risk-averse and more hesitant to join the riot. This means that some individuals may be willing to join very early, when the risk of being caught is high, while others may not be willing to join until the activity is very safe. To deal with this heterogeneity, Granovetter & Soong (1983) assign each individual a low or high threshold, representing the minimum number of other individuals who need to have joined the riot — or any other activity for that matter (see Rogers, 1962) — to allow the individual to join as well.

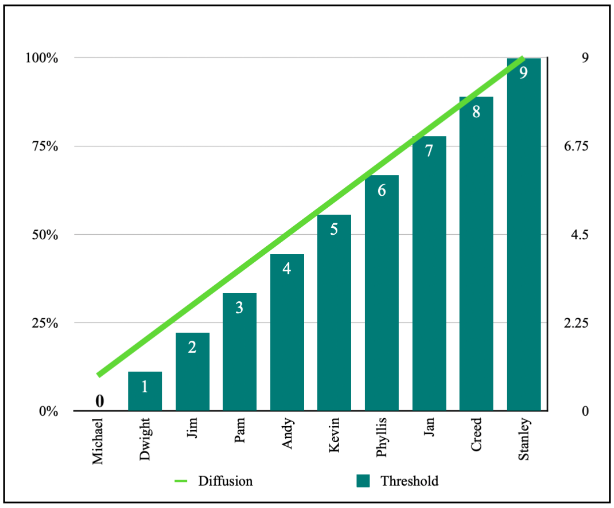

Figure 2.1: Granovetter and Soong's (1983) participation threshold model.

Figure 2.1 shows a simple example of Granovetter and Soong's (1983) participation threshold model. In this example, Micheal is the regional manager at a small paper company. To increase sales, he has the idea to hide coupons for a 10% deduction inside the next charge of paper deliveries. He now tries to convince his team of this idea at a marketing meeting. As Micheal is the initiator of the diffusion process, he has a threshold of zero. He is at the centre of the diffusion and fully convinced of his idea. Dwight joins second as he has a threshold of one, meaning that he needs at least one other person to adopt the idea before he can adopt it himself. After Dwight got convinced, Jim decides to support Micheal's idea as well. With two of his coworkers supporting the idea, his threshold of two is fulfilled. Now Pam joins as the fourth member of the group, then Andy, until even Stanley adopted Micheal's idea and the whole team is convinced.

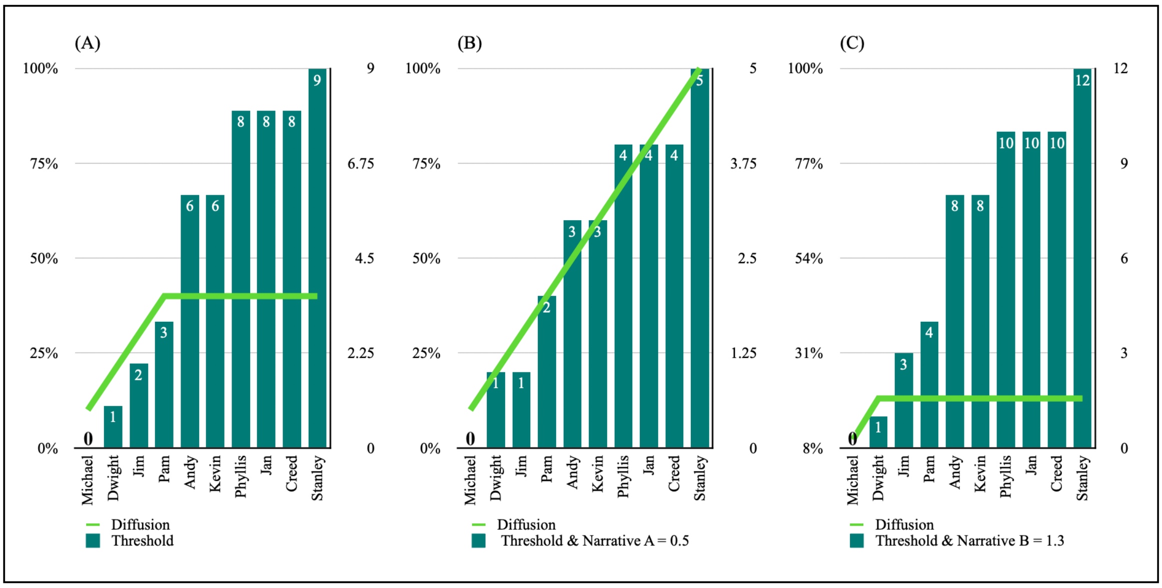

Figure 2.2: The effect of persuasiveness on Granovetter and Soong's (1983) participation threshold model.

Figure 2.1 shows a straightforward approach to Granovetter and Soong's (1983) participation threshold. In reality, thresholds are not linearly distributed, and a large population rarely reaches a diffusion of 100%. Figure 2.2 (A) shows a more realistic distribution of thresholds. Here, Micheal's idea is not adopted by all team members since Andy's threshold of six can not be reached. For all team members that have not adopted Micheal's idea, the number of participating individuals cannot outweigh the perceived risk of participation. Maybe all coupons end up at the same customer, and the company loses a significant share of that account, so that the team will have to take the blame for Micheal's bad idea.

The threshold model presented in fig. 2.1 and fig. 2.2 (A) is structurally innocent due to the simplifying assumption that each individual reacts to others disregarding who they are or what they are being asked to participate in (Granovetter & Soong, 1983, p. 175). Besides character traits such as risk adversity, an individuals threshold depends on several other factors, such as interests and belief system (Granovetter & Soong, 1983). For example, left-leaning individuals will be transported by a leftist narrative more easily than right-leaning individuals. It is, therefore, possible that different narratives face different thresholds, even though they are diffused in the same population. Therefore, it can be argued that the diffusion of a narrative does not solely depend on the number of individuals who have already been transported by it but also on different factors, such as how persuasive the narrative is. Ma, Feng, & Lai (2018) explore this idea and construct a model to predict the popularity of social media messages by combining measurements of the degree of diffusion and message attractiveness. Ma et al.'s (2018) findings support the idea of including a factor representing narrative persuasiveness to better conceptualise the diffusion of narratives.

Figure 2.2 (B) demonstrates the effect of narrative persuasiveness on the participation threshold. Assuming that individuals have a baseline threshold in relation to the content of a narrative, depending on their character traits, interests and belief system. Rhetoric tools can positively or negatively affect the baseline threshold. Figure 2.2 (A), (B), and (C) all show the same threshold baseline. However, while (A) takes no effect of narrative persuasiveness into account, (B) and (C) show how the baseline can be affected by persuasiveness. The diffusion in (B) only reaches 40%, while (B) shows diffusion of 100%. Even though the narrative content is the same in both cases, this thesis expects that rhetoric tools can affect the persuasiveness of narratives. As shown in (C), some individuals may perceive some rhetoric tools negatively. For example, Jones & McBeth (2010) describe how narratives are actively rejected in cases where they lack congruence. Additionally, Boswell et al. (2011) point out that narratives are less successful if they lack some basic cognitive requirements. Figure 2.2 (B) and (C) simplify the effect of persuasiveness on narrative diffusion as both figures assume that the persuasiveness of a narrative is constant across all individuals of a population. This is not true, individuals will be affected differently by the same rhetoric tools. However, For the sake of simplification, this instance will be ignored.

The advantage a narrative gets from a high degree of diffusion is that the number of transported individuals will become so large that persuasiveness might play a decreasingly important role in the diffusion of the narrative. As Margetts et al. (2016) point out, at the beginning of the diffusion process, people with very low thresholds are needed to start a mobilisation. From the perspective of a political actor with strategic intentions, it is desirable to reach those individuals first and construct persuasive narratives, for example, by addressing controversial topics that breach canonicity (Jones & McBeth, 2010), or construct trustworthy narratives that rely on expert knowledge and appear valid (Boswell, 2008). Once sufficient individuals with low thresholds are transported, they will encourage individuals with slightly higher thresholds. This enables the narrative to reach individuals with even higher thresholds. Assuming that thresholds within a population are distributed normally (Schelling, 2006), the narrative will eventually transport enough people so that diffusion will reach a tipping point (see fig. 2.3). Now most people's thresholds lie at or below the degree of diffusion. This will trigger a flood of individuals who will be transported by the narrative (see Margetts et al., 2016).

The following paragraphs will discuss the dynamics within a social network, such as the Twitter network. This will help understand how narratives diffuse in the context of thresholds and network access. The complex nature of the data at hand demands a fundamental understanding of how individuals interact in social networks as the interactions are very rudimentary, fast and short-lived. Furthermore,

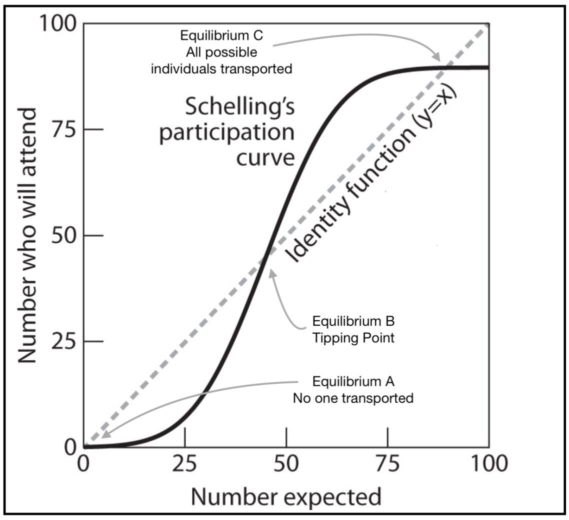

Figure 2.3: Schelling's (2006) participation curve (Margetts et al. 2016, 178).

interactions on Twitter are different from real-life interactions, so a conceptualised understanding of such interactions needs to be provided.

Even though fig. 2.4 shows a simplified network graph, it becomes clear that social networks consist of multiple communities with different dynamics and relationships. In the case of Twitter, two kinds of relationships can be distinguished. A 'follower' relationship and a 'friend' relationship. While friend relationships allow both individuals to observe one another, follower relationships allow observation only in the direction from the follower to the followee. Thus, each node in the graph can be assigned an in-degree and an out-degree. The out-degree shows the number of arrows that point away from the node, and the in-degree is equal to the number of arrows that point toward the node. Therefore, the in-degree represents the number of other users that observe the individual associated with a node, and the out-degree represents the number of users observed by the individual. For example, Micheal has a degree centrality of [4,1], meaning that the in-degree of his local network is four while its out-degree is one. Thus, Micheal follows one person and is friends with four. It becomes clear that real social networks, such as Twitter, provide a much more difficult population to penetrate than the participation model assumes (Granovetter & Soong, 1983). Stanley, for example, cannot be reached at all. His degree centrality is [2,0]. Even though Stanley is observed by Phyllis and Creed, he does not observe anyone in the network. Thus, he can pass on information to the network but can not be reached by information from the network.

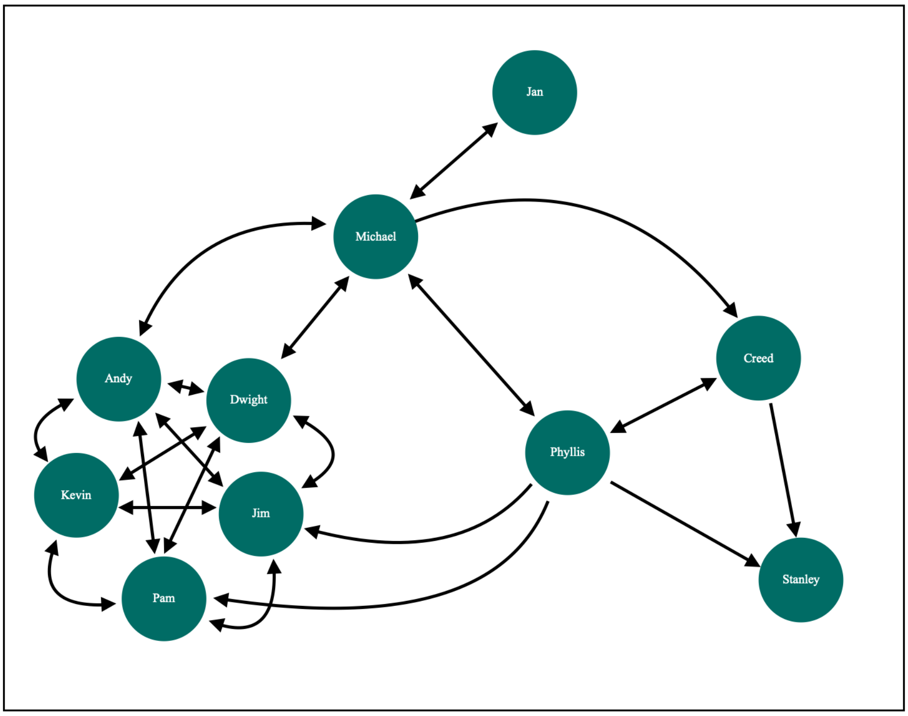

Figure 2.4: Representation of a social network.

Individuals can be members of more than one community. Phyllis' local network, for example, has an out-degree of five and an in-degree of two, which means that she follows five people and is friends with two. In other words, Phyllis observes five people but is observed by only two people. Thus overall, her local network influences her much more than she influences her local network. To bring Phyllis past her threshold of three, three individuals in her local network need to be transported by the narrative. Going back to the example of Micheal's coupon idea, he could pass this idea on to Andy, Dwight, Phyllis, Creed and Jan. Assuming that Andy and Dwight are successful in reaching Jim and Pam, who are part of their local network, Phyllis will now have three people in her local network who adopted Micheals idea and will adopt it herself. This, in turn, will affect Creed, who now observes two individuals who adopted Micheals idea. Thus, the argument can be made that both the structure of local networks and global networks affect the propensity of narratives to diffuse.

2.4 Knowledge Claims

Policymakers encounter data, science, and evidence on a daily basis to deal with uncertainties of increasingly complex policy problems (Jasanoff, 2004). However, the growing importance of evidence and knowledge in policy does not mean that policymaking is purely technocratic. A large part of policymaking responds to popular pressure or sticks to the wisdom of practitioners and bureaucrats (Boswell et al., 2011; see Stone, 1988). Nonetheless, the expectation that policymakers have expert knowledge and research available to inform decision-making influences the construction of narratives (Boswell et al., 2011). This means that the knowledge generated by experts influences the perception of policy problems and their solutions (Weiss, 1979).

Research and expert knowledge often have a more symbolic function in policymaking. Knowledge claims may enhance the competitiveness of narratives by increasing the legitimacy of actors and organisations or disarm political opponents (Boswell, 2009). Furthermore, Timmermans & Scholten (2006) point out that expert communities or policy advisors can introduce new problems to the public debate or, according to Majone (1989), make previously controversial ideas acceptable and available for discussion. Building on this understanding, this thesis conceptualises knowledge claims as rhetorical tools that are strategically deployed within a narrative to increase its persuasiveness. They give the impression that the discussion substantially revolves around the causes, dynamics, and effects of a given policy problem (Boswell et al., 2011). Thereby rhetorically disconnecting the validity of a narrative from the subjectivity of the actor. This, in turn, has the potential to increase narrator trust and make a narrative more persuasive (see Jones & McBeth, 2010).

However, to make a narrative more persuasive, Boswell et al. (2011) point out several minimum requirements that have to be met. Narratives must meet certain minimum conditions of consistency, coherence and plausibility (Boswell et al., 2011, p. 2). In some cases, adherence to scientific validity requirements is a prerequisite as well. Furthermore, a narrative ought to establish causal relationships between actions and events (Banerjee, 1998; Roe, 1994). Additionally, narrator trust can not be generated when narratives go against the available knowledge, and they must align with available information. This is not to say that narratives can not go against the perceived status quo, but rather that narratives must adhere to what is thought to be known. According to Boswell et al., the final criterion is that the narrative "must be understandable, compelling and sufficiently plausible for the actors in question" (2011, p. 6). This instance is related to Jones & McBeth (2010) concept of congruence, which states that narratives must be formulated in a way that is understandable in order to be persuasive. They must be formulated in a language that the listener understands and can relate to. If this is not the case, the narrative is actively rejected (see Jones & McBeth, 2010). Knowledge claims play a central role in providing such requirements and offer a way to put parts of a narrative, or the narrative as a whole, in an empirical context. Thus, strengthening statements about the causal relationships and mechanisms at play. This frequently puts them in the focus of criticism because of their failure to meet these requirements (Boswell et al., 2011, p. 2).

2.5 Research Question and Hypothesis

According to Boswell et al. (2011, p. 1), political actors often utilise knowledge claims in political communication. Opposing actors use knowledge claims differently and engage in competition for the validity of their narratives among their peers (Boswell et al., 2011). Gupta et al.'s (2018) findings support the assumption that actors engage in competition for support on social media platforms like Twitter. Winning actors use narratives to contain the scope of conflict, whereas actors that are losing use narratives to expand the scope of conflict (Gupta et al., 2018, p. 17). Thus, it is reasonable to suspect that the competitive use of knowledge claims in EP narratives affects their diffusion on Twitter.

The paper aims at answering the following research question: "How do knowledge claims affect the diffusion of English language tweets authored by European Parliamentarians between 2017 and 2019?" This thesis aims to estimate the effect of knowledge claims on the diffusion of narratives in a political context on Twitter. As this research follows a positivist approach, the following hypotheses are formulated:

H1: Knowledge claims found within EP tweets are associated with a higher count of retweets.

Hypothesis one refers to a positive effect of knowledge claims on retweet count. As discussed in the operationalisation section above, retweet count is drawn from to infer the degree of diffusion exhibited by a narrative represented in a given tweet.

H2: The effect of knowledge claims on original tweets is different to the effect on retweets.

Hypothesis two states that there are differences found among tweets representing an original narrative, i.e. not a reaction on another tweet, potentially another EP, and those tweets that are reactions to existing tweets and the discussion surrounding them. As Gupta et al. (2018) point out, actors may seek to increase the scope of conflict for strategic reasons. Thus, it is more likely to find such a strategy in reactions to other users. Actors may use knowledge claims to disarm opponents. This is expected to cause differences in the diffusion of narratives on Twitter.

H3: The effect of knowledge claims on retweet count varies with

party family affiliation of the EP.

Jones & McBeth (2010) suggest to anchor analysis of narratives in quantifiable context, such as party families. Therefore, this thesis expects measurable differences in the use of knowledge claims across party families.

Chapter 3

Research Design

In the following, the theoretical framework above shall be operationalised to provide grounds for the quantitative method. The data selection will be based on Twitter data of social media messaging of EPs. This will make it possible to inductively reason how knowledge claims affect retweet count and establish an understanding of this effect. To measure this effect, this thesis applies several OLS regressions on log-transformed data.

3.1 Data Collection

First, the following section will present the Twitter Parliamentarian Database (TPD) constructed by van Vliet et al. (2020). This serves the purpose of identifying the challenges and merits of the dataset. Secondly, the construction of the European Parliamentarian subset will be discussed. The subset will filter out all English language tweets authored by EPs. Limiting the language to English will provide a way of validating the two 'keywords in context' algorithms (see Benoit et al., 2018), which are deployed to infer topics across groups of tweets corresponding to the keyword search through hashtag use. This serves the purpose of validating the keyword search.

The section will then end by providing descriptive statistics of all variables introduced for analysis.

3.1.1 The Twitter Parliamentarian Database

Twitter is the social media messaging platform of choice for political actors, which brings the potential of being a data source non plus ultra for social scientific research (Lazer & Radford, 2017). Indeed, a query of the keyword combination 'Twitter' and 'politics' retrieves a growing body of scientific articles written between 2018 and 2019 from the web of knowledge database, roughly one article every three days has been published in this period (van Vliet et al., 2020, p. 2). However, despite this increase in literature on the use of Twitter data for social science research, there remain some fundamental issues in terms of delineation, sampling, and validation (van Vliet et al., 2020, p. 2).

According to Tufekci (2014), in research scrutinizing politics on Twitter, population delineation is inadequately addressed. In other words, some basic assumptions about the representativeness of the population through samples of Twitter data do not hold or are at least questionable. Van Vliet et al. (2020) point out that quantitative research often assumes that the sample consists of users who index their tweets with hashtags or keywords in a way relevant to the population (e.g., Dubois & Gaffney, 2014). However, van Vliet et al. (2020) point out that the use of hashtags and behaviour of Twitter users is inconsistent and does not allow for an understanding of the population. Hashtags of users participating in debates are not necessarily used in a way consistent with the research question (van Vliet et al., 2020). Additionally, users who do use relevant hashtags do not always participate in the examined discussion (van Vliet et al., 2020). This raises concerns about how to distinguish between signal and noise (Marrens and Moats, 2015. Cited after van Vliet et al., 2020).

According to van Vliet et al. (2020), the selection of a panel based on hashtags is not optimal. Due to the arguments above, identifying a representative sample through the use of hashtags by Twitter users remains arbitrary to an unknown extent, which makes for arbitrary results as well (van Vliet et al., 2020).

The authors van Vliet et al. (2020) point out two additional challenges. Firstly, the consistently changing Twitter API and differences between the free and paid version make for troubling implications of comparing and replicating results derived from Twitter data (van Vliet et al., 2020). By querying the API by hashtags or keywords, it has been shown that not all available tweets can be gathered by Twitter's free API (van Vliet et al., 2020). Furthermore, the in-transparent sampling process by Twitter makes it difficult to identify which tweets have been selected for the sample and which did not. This makes it challenging to address biases in the resulting data (see Morstatter et al. 2013; Joseph et al. 2014; Bruns and Liang 2012. Cited after van Vliet et al., 2020). However, this issue can be addressed by focussing the sampling process on a specific group of users (van Vliet et al., 2020). Rauchfleisch and Metag (2016. Cited after van Vliet et al., 2020) have shown that by querying specific groups of Twitter users, all tweets belonging to these users can be retrieved to produce a complete sample according to the set sampling parameters.

Secondly, it is challenging to connect Twitter data to other meaningful data sources (van Vliet et al., 2020). In a social science setting, the challenge is to provide additional information about, for example, political orientation. Researchers have addressed this issue by inferring users' political views through analyzing follower or friend networks and hashtags (van Vliet et al., 2020). However, this can only be suboptimal as the use of hashtags and the choice of followers and friends is inconsistent among users. Therefore, it may produce false positives and identify only a subset of all users with a particular political viewpoint (van Vliet et al., 2020). Furthermore, as Twitter prohibits the algorithmic identification of political viewpoints, scholars have to develop more sophisticated methods, such as linking Twitter data to survey data (van Vliet et al., 2020).

van Vliet et al. (2020) present a solution to the challenges discussed above by sampling parliamentarians with known party affiliations and linking Twitter data to existing databases for additional information. The resulting database is a multi-source and manually validated database of parliamentarians on Twitter (van Vliet et al., 2020). The TPD comprises parliamentarians from all members of the European Free Trade Association, with over 45% of parliamentarians on Twitter and a variety of English-speaking countries (van Vliet et al., 2020). The database is intended to step in the direction of comprehensive and transnational study beyond the unique scope of most Twitter-based studies (van Vliet et al., 2020). In addition to data obtained from Twitter's API and government websites, the TPD integrates data from the Manifesto Project Database, the Electoral Framework Architecture Database, the ParlGov database, and the CHES (van Vliet et al., 2020).

3.1.2 European Parliamentarian Subset

For this thesis, a subset of the TPD was constructed (see table 3.2). As described above, it is necessary to limit variability within the data to gain insights into the effect of knowledge claims on narrative diffusion on Twitter. Thus, the TPD was reduced to a subset of 583,780 observations containing only members of the European Parliament.

Furthermore, the data has been limited to English language tweets. Limiting the observations to English language tweets helped validate the keyword search and controls for any effects language might have on retweet count. It is possible that a German tweet might achieve a lower retweet count than an English one, as English is more widely spoken and understood by the Twitter audience. One has to keep in mind that not only Europeans are expected to participate in the diffusion of narratives on Twitter. Twitter is a global platform. To control for this effect across all languages spoken by EPs in the sample, languages other than English have been excluded.

However, focusing on English language tweets brings about another challenge. Namely, how to deal with EU countries native to English? By excluding other languages, a bias toward the EU languages who communicate primarily in English is generated (see fig. 3.1]. BesidesIreland and Malta, the UK, in particular, has to be considered as a potential source of bias since UK tweets make up the largest part of total EP tweets in the TPD overall as well as among recorded English language tweets (see fig. 3.2).

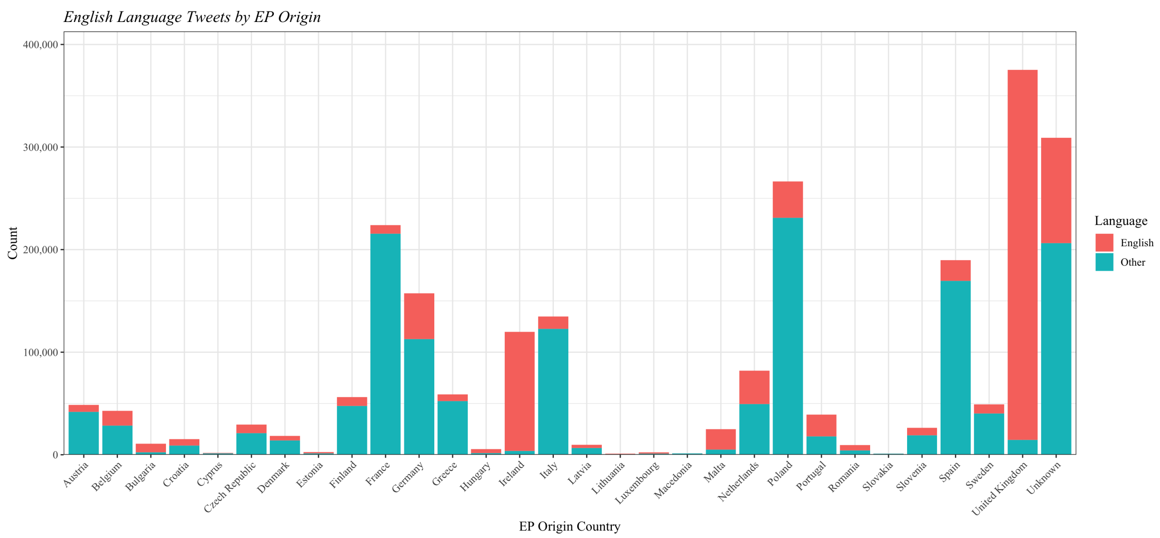

Figure 3.1: English language tweets by EP origin country.

Another bias can be identified regarding the distribution of CHES party families by EP origin country. As the UK produced the most tweets in the data at hand, the CHES family distribution among UK tweets must be considered when constructing linear regression models. Figure 3.2 shows that, according to the party families identified by the CHES, compared to the rest of the EU, tweets by radical right-wing UK EPs make up a large portion of the total tweets measured by van Vliet et al. (2020). Thus, potentially distorting the results of the regressions below.

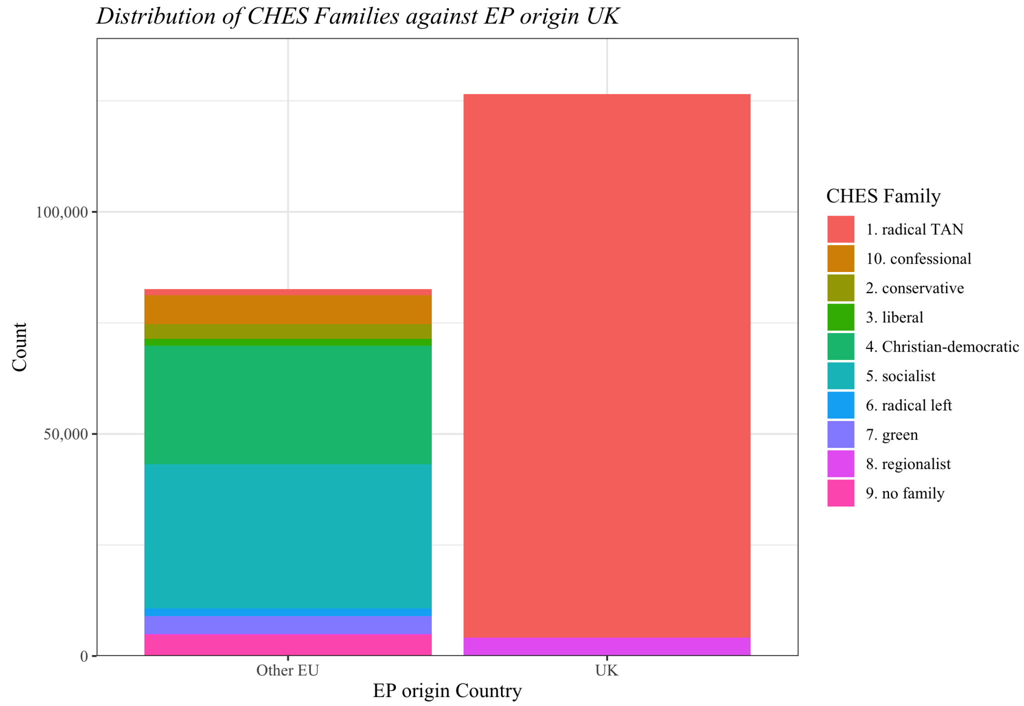

Figure 3.2: Distribution of CHES party families against EP origin UK.

Party Families

van Vliet et al. (2020) make use of two political data sets to enrich the collected Twitter data with information on party families. Firstly, the ParlGov (Döring & Manow, 2012) and, secondly, the CHES (Polk et al., 2017). The number of party family observations within the data subset is 270,634 for the ParlGov, and 209,114 for the CHES. To scrutinize the effect of knowledge claims across party families, this thesis chooses the CHES dataset for the following reason.

Even though the ParlGov shows more observations in the dataset at hand (see fig. 3.3), the CHES provides more recent measurements of party families. The ParlGov data available in the TPD was collected in 2012, while the CHES provides data from 2017. Furthermore, according to (Polk et al., 2017), party families measured by the CHES are based on the Derksen classification triangulated by party membership or affiliation with European Parliament families, self-identification, and ParlGov classification. As the CHES also makes use of the ParlGov classifications, in addition to other data sources, the CHES is expected to deliver higher accuracy and provide a superior understanding of EP party families.

Combining both data could potentially provide 292,459 observations; however, filling the gaps of one data set with another is expected to cause discrepancies. The ParlGov and the CHES classify party families with different methodology and use different categories. The ParlGov distinguishes between nine different categories and the CHES between ten. Migrating data from one data set to the other is expected to require an in-depth understanding of the classification methods applied in both cases. Thus, this thesis will disregard the ParlGov data provided by the TPD and focus on CHES party families.

The CHES observations allow differentiation of ten party families:radical right (radTAN), conservative (cons), liberal (lib), Christian democratic (chrDem), socialist (social), radical left (radLeft), green (green), regionalist (regio), confessional (confessional), and finally a category for cases where no family could be identified (noFam). Additionally, the CHES provides another category, namely agrarian/centre (Polk et al., 2017) to these ten categories found in the data at hand. However, no observations of this category were counted in the TPD subset considered for analysis. Therefore, this category shall be disregarded.

As fig. 3.3 shows, the ParlGov only provides additional information for the party families conservative and green. All other categories contain data to toward the same level except for the categories confessional, christian democratic, and regionalist. It could definitely be argued for the ParlGov data set as the superior source of data on party families. However, for this the reasons explained above, this thesis considers the CHES for analysis.

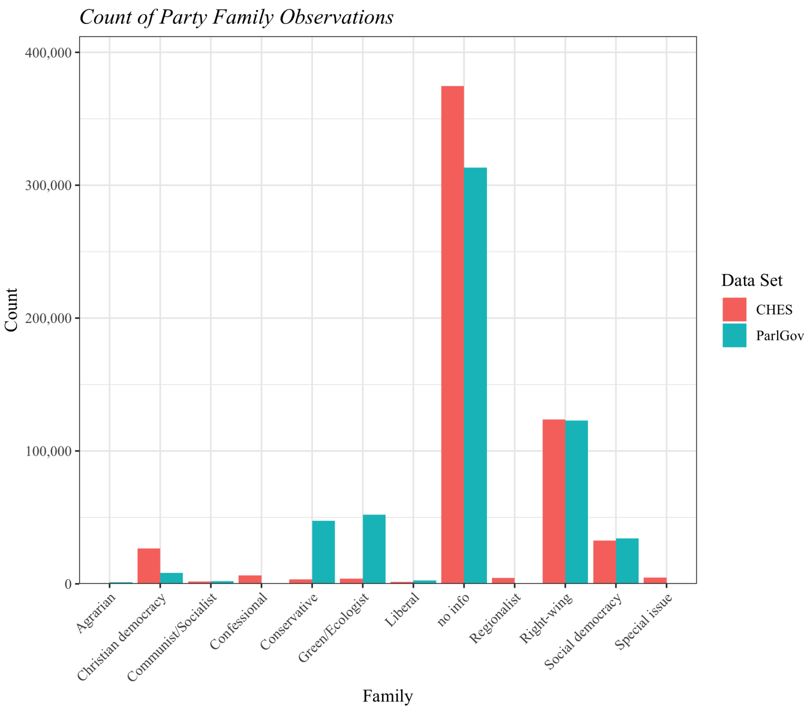

Figure 3.3: Distribution of party families.

3.2 Operationalisation

Firstly, a couple of basic terms related to Twitter as a platform should be clarified before going into other aspects more deeply. Individuals who have a Twitter account are referred to as *users*. Sometimes the use of the terms 'user' and 'individual' will be applied interchangeably. However, they will be used in contrast to the term 'political actor.' The political actors observed in the data, also referred to as EPs, are also Twitter users. However, they play a different role in the diffusion process and are, thus, not referred to as 'users,' but as *actors*. The term *follower* means a unidirectional connection between two users in the Twitter network, where the follower observes the followee, but not the other way around. The term *friend* refers to a bi-directional connection. Here, both parties can observe one another. A number of followers and friends create a local network located within the global network of all users. A *tweet* is a social media message on Twitter. These messages are authored by one user and passed on to their local network of followers and friends. *Retweets* are instances where a user has shared an existing tweet to his or her local network. It is essential to consider that, even though the user has not authored the message by themselves, they can react to it in the form of an attached message but do not have to. The following paragraphs will go on to explain the dependent and independent variables as well as the controlling variables.

As described above, the term *narrative* refers to strategic rhetoric surrounding political messages. This thesis assumes that social media messaging of political actors, such as EPs, always serves to communicate political messages. These messages aim to persuade other people toward a change in perception, in other words, transport them (Charteris-Black, 2011; see Jones & McBeth, 2010). Thus, narratives will be operationalized as social media messages or tweets authored by political actors, such as EPs.

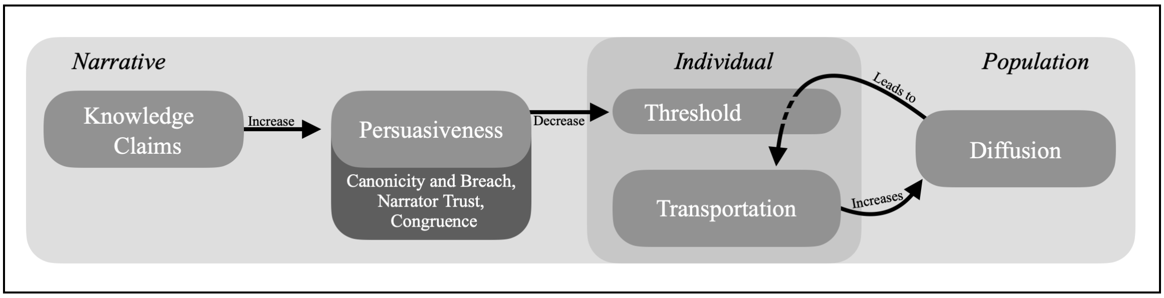

Figure 3.4: Relationship of variables.

Figure 3.4 shows the role of narratives, or tweets in this case, in the diffusing process. Narratives affect individuals by decreasing the perceived threshold to adopt the underlying message of the narrative. By adopting the message and being transported by the narrative, the individuals contribute to the diffusion of the narrative. In the context of Twitter, this happens by retweeting. Once an EPs tweet reaches the individual, they resonate with it in some way and decide whether to react to it or not. Figure 3.4 suggests that two factors influence the individual's decision, firstly, the narrative and its condition concerning persuasiveness, and secondly, the population's perceived reaction to the narrative.

Diffusion is defined as the degree to which a population has been transported by a narrative (see section 2.3). Whenever a tweet gets retweeted by a user, Twitter records this and makes it accessible through its API (application programming interface). Accordingly, retweet count makes for a precise measurement of how many users have seen the narrative, reacted to it somehow, and took action to spread it among their local networks. This study refers to this process as transportation (see Jones & McBeth, 2010). As pointed out earlier, it is not part of the scope of this research to distinguish whether a retweet was meant to be positive, negative, satirical, or was produced artificially (retweeted by a computer program). This means that it is not possible to distinguish between those retweets that resulted from a persuasive process in the sense of Charteris-Black (2011), who only considers an individual persuaded if he or she changes in a way that was intended by the actor and those who rejected the message of the narrative. However, this thesis does not need to distinguish between positive and negative reactions to a narrative. Both can be considered transportation in a minimal sense. That is to say that, regardless of whether a retweet was meant to be negative or positive, the narrative resonated with the individual and changed them, i.e. transported them, in a way that motivated them to take action and contribute to the diffusion of the narrative — something they would not have done if there was no change in perception. Diffusion, or retweet count, is the dependent variable considered in this study.

The independent variable examined in the empirical section is knowledge claims. As discussed above, knowledge claims are expected to affect the persuasiveness of a narrative by increasing factors like narrator trust (see fig. 3.4). Knowledge claims will be operationalized via a keyword search of 22 keywords:

> *expert*, report-, reports, report, think tank, thinktank, think-tank-, statistic*, study*, research*, institute*, evidence*, evident*, science*, analy*, calcul*, data*, examin*, investigat*, estimate*, scientif*, studi*.*

The keyword search resulted in 25,772 tweets associated with at least one of the keywords, roughly 5% of the entire data set. The keywords were selected deductively based on Carpenter's (2010) definition of technical reputation. Technical reputation refers to the capacity of an actor to call him- or herself an expert on a given problem and determines whether or not an actor is qualified in a "professional or rational sense" (Carpenter, 2010, p. 46). Carpenter identifies technical reputation as follows: "Technical reputation encompasses variables such as scientific accuracy, methodological prowess, and analytic capacity" (2010, p. 46). This approach provides a simple and straightforward way of differentiating between EP tweets containing knowledge claims and those that do not.

To operationalize the theoretical framework, this thesis has to make a case for the quantifiability of narratives in social media messaging of political actors. To solve this problem, narratives must be anchored in generalizable content (Jones & McBeth, 2010). Accordingly, tweets will be viewed in the context of party families. The use of information on political positions to identify variation in the use of rhetoric on Twitter is supported by Weber & Garimella (2013), who could measure differences in the use of hashtags, or keywords, across the Islamist vs secular cleavage in Egypt.

Viewing tweets constructed by parliamentarians in the context of affiliation to a party family provides a strong anchor for positivist research as actors are likely to use different plots, characters, and causal mechanisms depending on their party affiliation (Jones & McBeth, 2010). van Vliet et al. (2020) use two political data sets to enrich the collected Twitter data with information on party families. Firstly, the ParlGov (Döring & Manow, 2012) and, secondly, the CHES (Polk et al., 2017). To scrutinize the effect of knowledge claims across party families, this thesis chooses the CHES dataset. Section 3.1.2 discusses the reasoning behind choosing the CHES over the ParlGov.

The social network on Twitter, which is made up of users and following relationships, has gotten much attention in the past as a possible predictor of political influence (see Dubois & Gaffney, 2014). The basic reasoning behind the potential to identify influence through Twitter's social network seems straightforward: Twitter users will shape following relationships only with people whose tweets they expect to read, internalize, and discuss. However, previous research has discovered that a static interpretation of a network of follower followee relationships is only a poor predictor of narrative penetration, i.e. diffusion. Both Kwak, Lee, Park, & Moon (2010) and Cha et al. (2010) looked into the relationship between a Twitter user's number of followers and their influence and discovered a significant difference between the most-followed and most-retweeted individuals. As a result, this study strongly suggests that the number of followers alone does not accurately represent the overall penetration of Twitter's social network and considers retweet count an essential component of the study of narrative diffusion on Twitter.

Ma et al. (2018) show that a tweet's success in diffusion and retweet count can be predicted by considering several variables, such as status count, follower count, and friends count. Information on these variables is conveniently provided through the Twitter API and available in the data set at hand. Follower count, statuses count, friends count, and verified status will be considered as controlling variables. *Statuses count* refers to the number of tweets a user has. Thus, statuses count represents the activity of a user on Twitter. The statistical models below will consider statuses count as a controlling variable because it is possible that more active individuals with generate more 'buzz' within their local networks and, thus, reach more users, which may increase their average retweet count. *Friends count* represents the in-degree of the EPs local network. Because friends follow each other and observe each others activity, it is crucial to consider this variable as a controlling variable. The in-degree is part of the degree centrality of a user and shows the impact of the users local network on the global network. More connected EPs potentially generate more retweets, affecting the dependent variable ‘diffusion.’ For the same reason, this research considers followers count as a controlling variable. Like friends count, followers count represents the in-degree of the local network of the EP. Considering the number of users the EP follows, i.e. the out-degree, is not essential for this study as the number of followed users does not affect the visibility of the outgoing tweets.

3.3 Exploration

To confirm the result of the keyword search, a word cloud was constructed. The word cloud (fig. 3.5) is separated into two parts according to whether a tweet corresponds to a category ‘knowledge claim’ or not. Figure 3.5 shows hashtags exhibiting category no knowledge claims in light blue and hashtags of tweets exhibiting knowledge claims in dark blue. The further a tweet is positioned away from the middle, the more prominently it is used in the respective category (see Benoit et al., 2018). At the same time, the word size resembles the frequency of the hashtag.

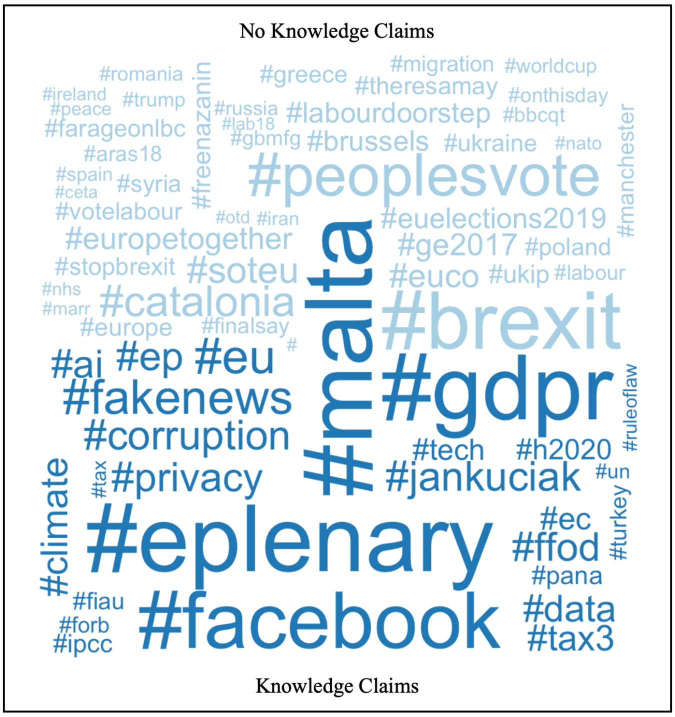

Figure 3.5: Hashtag word cloud

Figure 3.6 provides further information about the frequency of hashtag use in each category. Group 0 shows hashtags found in tweets containing no knowledge claims, and group 1 shows hashtags found in tweets containing knowledge claims. According to the shown, frequencies are calculated in percentages relative to the respective size of each group. Compared to the word cloud in fig. 3.5 hashtag frequency was estimated using a different algorithm (see Benoit et al., 2018). In the case of the word cloud, frequency across groups was estimated considering the dataset as a whole, while the frequency in fig. 3.6 was estimated considering each group by itself. Therefore, some discrepancies can be identified. For example, the hashtag #eu is estimated to appear more frequently in the context of 'non-knowledge claim' tweets, while it is shown to belong to the category' knowledge claim' in the word cloud. Additionally, some hashtags appear in figure 6 that do not appear in the word cloud, for example, #panampapers. However, as this is due to different measuring techniques, both figures can be drawn from when validating the keyword set.

Keeping the difference in measuring techniques in mind, it appears possible to validate both visualizations to each other. When considering some of the most prominent hashtags, #brexit, #eplenary, and #malta, it appears that both algorithms identified them to belong to the same category. Additionally, the relative difference in group frequency (fig. 3.6) of these hashtags seems to infer the positioning of those hashtags within the word cloud correctly. Hashtags, more frequently used in one category, are positioned further away from the centerline of the word cloud (fig. 3.5). This appears to be especially true in the case of hashtag frequency the hashtag #facebook, which does not appear in group 0 of the hashtag frequency estimation at all (fig. 3.6) and is positioned furthest away from the word cloud centerline (fig. 3.5) within category' knowledge claim.

After validating the word cloud (fig. 3.5) against the hashtag frequency esti-

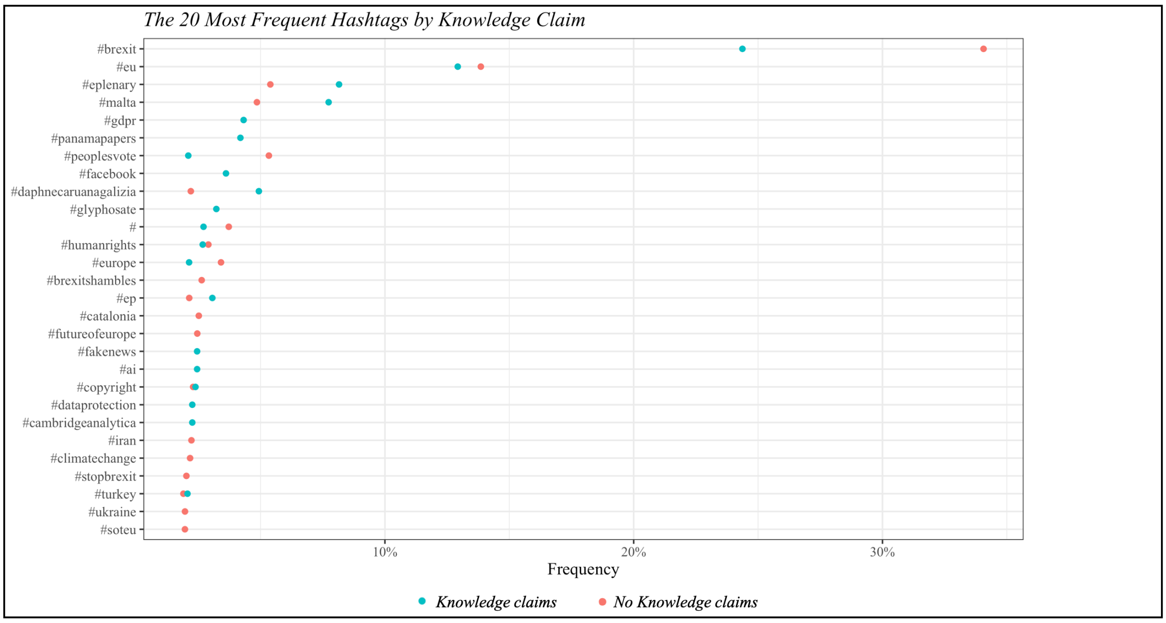

Figure 3.6: Top 20 most frequent hashtags

mation (fig. 3.6), the following paragraphs will discuss hashtag use across categories using the word cloud as this visual provides a complete picture of topics used within each category, inferred by hashtag use. Hashtags found in tweets without knowledge claims are, for example, #brexit, #catalonia, #syria, and #migration. Assuming that hashtags allow inferring the content of those tweets, it can be said that topics referring to nationalist or populist topics like the EU exit of the UK and migration are more like to be found in tweets that do not refer to knowledge claims (Browning, 2019; see Verbeek & Zaslove, 2017). Additionally, tweets referring to politicians (#farageonlbc, #trump and #theresamay) are exclusively found within the category 'no knowledge claims.' This might be explained by the proximity of Nigel Farage and Theresa May to the topic 'Brexit,' which is exclusively featured on the 'no knowledge claims' side of the word cloud. The populist politics of Donald Trump (Inglehart and Norris 2019) may explain why the hashtag '#trump' is found among populist topics like #peoplesvote and #catalonia, which may refer to a 'people vs the elite' narrative found in populism (Mudde & Rovira Kaltwasser, 2017). According to Mudde & Rovira Kaltwasser (2017), the 'people's power' to organize and, through collective action, stand up to the 'elite' is associated with populism. Assuming that #peoplesvote asks the 'people' to collectively take action and vote for a greater good, a narrative described by Mudde & Rovira Kaltwasser (2017), and that #catalonia refers to the separative agenda of Spanish nationalist actors such as the Catalan independence movement (see Crameri, 2015), this thesis associates populism with the keyword category 'no knowledge claim.' Meaning that populist narratives are less likely to contain knowledge claims.

On the other hand, the word cloud category' knowledge claim' contains hashtags referring to policy problems such as data privacy, climate change, and corruption (#gdpr, #climate, and #corruption). A possible explanation for the hashtag '#fake news' in the context of knowledge claims is the attempt to disprove supposedly false information distributed by political opponents through references to empirical evidence. This argument is supported by Boswell et al. (2011) conceptualization of knowledge claims as competitive elements of narratives. As discussed above, Boswell et al. (2011) point out that political actors utilize knowledge claims to provide empirical grounding to their narratives and make them more persuasive. Accordingly, references to 'fake news' would be more likely to appear in the context of knowledge claims.

Additionally, hashtags referring to technologies appear more commonly in the context of knowledge claims (ex. #data, #ai, and #tech). According to Stone (1988, p. 3), scientists, health professionals, and engineers may provide analysis, knowledge, and advice to policymaker to enhance decision-making processes. Stone (1988) refers to this phenomenon as 'technology for science.' In contrast, policymakers also take action to influence the science and technology community to engage in research regarding a particular policy problem such as climate change (#climate, #ipcc) in a process, Stone (1988) coins' policy for technology.' At the same time, policymakers may also influence business-related activities, for example, patent law

Stone (1988). Additionally, Lodge & Wegrich (2012, p. 63) point out that technology is also a central part of regulatory standard-setting. In this context, policymakers are concerned with prescribing particular technologies, for example, the use of LED lightbulbs (Supplementing Directive 2010/30/EU of the European Parliament and of the Council with Regard to Energy Labelling of Electrical Lamps and Luminaires Text with EEA Relevance, 2012), or provide specifications of technologies (Lodge & Wegrich, 2012).

To summarize, the constructed word cloud is able to provide topical distinctions among narratives containing knowledge claims and those that do not. It appears that the knowledge claim category contains mostly topics that are related to specific policy issues, such as climate, GDPR (data privacy), tax, technology, and corruption. In contrast, politically loaded topics, such as elections, parties (UKIP, Labour Party), politicians (Nigel Farage, Theresa May), migration, Brexit, are more likely to appear in the context of the 'non-knowledge claim' category.

3.4 Descriptive Statistics

This section will present descriptive statistics of all variables considered in this study to provide transparency into the data at hand. Table 3.2 shows descriptive statistics of all continuous variables relevant to the linear models below, while table 3.1 shows a description of the categorical variables.

Table 3.1: Descriptive statistics of categorical variables.

Statistic	N	Obs. Share	Avg. Retweets	Know. Claim Ratio
is_uk = 1	261,186	0.44	295.79	0.0329
is_uk = 0	322,594	0.56	351.66	0.0533
original = 1	239,470	0.41	42.56	0.0418
original = 0	344,310	0.59	524.26	0.0458
exknow = 1	25,772	0.04	245.29	1
exknow = 0	558,008	0.96	330.42	0
radicalTAN	123,765	0.21	320.21	0.0244
cons	3,333	0.01	278.12	0.0414
lib	1,582	0.01	590.41	0.0411
chrDem	26,650	0.04	166.68	0.0613
social	32,452	0.05	559.11	0.0642
radLeft	1,753	0.01	121.46	0.0314
green	3,984	0.01	722.91	0.0705
regio	4,334	0.01	149.85	0.0344
confessional	6,486	0.01	91.80	0.0669
noFam	4,775	0.01	573.94	0.0542
Total	209,114	0.36	340.28	0.0404

Table 3.1 presents a description of each categorical variable, such as the dichotomous independent variable, knowledge claims (exknow). The upper section of table 3.1 shows all dummy variables, while the lower section describes the CHES party family categories. The 'Total' row summarizes each column of the party families section. The 'Obs. Share' column informs about the share of observations associated with each measurement. 'Avg. Retweets' shows the mean retweet count of each measurement, while 'Know. Claim Ratio' calculates a ratio between the number of knowledge claim tweets (exknow = 1) and the number of non-knowledge claim tweets (exknow = 0). For example, the 'radicalTAN' column indicates that per non-knowledge claim, there are 0.005 knowledge claim tweets associated with the right-wing party family *radicalTAN*.

When calculating the sum of each party family category, one realizes that column *N* does not add up to the total sample size of 583,780. As discussed in section 3.1.2, the TPD does not provide party family measurements for each observation. However, this should not pose any hurdles since the data still provides a sufficient number of measurements (N = 209,114). Additionally, because the overall average retweet count in row 'Total' is close to the average retweet count of the entire data set (see **??**), no biases in retweet count are expected when considering only part of the data set.

Table 3.2: Descriptive statistics of continuous variables.

Statistic	N	Mean	St. Dev.	Min	Max
retweet_count	583,780	326.667	4,811.562	0	1,550,243
user_followers_count	583,780	38,178.670	122,225.900	46	2,553,857
user_friends_count	583,780	4,254.552	5,230.780	0	30,575
user_statuses_count	583,780	50,429.870	48,150.040	27	185,210

Table 3.2 shows that the available data has measurements of retweet count, follower count, friends count, and status count for each observation (n = 583,780). This provides confidence about the completeness of the data provided by the TPD. When considering the minimum and maximum columns in table 3.2 compared to the mean, it becomes apparent that the data shows a right-skewed distribution. This circumstance suggests that the data is not normally distributed. In the case of a normal distribution, the data would show a mean closer to the number located halfway between minimum and maximum, in this case, 775,121. Normally distributed data would also show a median and mode located close to the mean. However, the median of the dependent variable retweet count is 9, while the mode equals 0. Additionally, the high standard deviation of all variables provides evidence against normally distributed data and suggests high variance in the data (s^2). Table 3.2 suggests a long tail in the data, which poses a statistical challenge to linear regression models (Raban & Rabin, 2009).

3.5 Method

After identifying possible biases in the data and validation of selected keywords in section 3.1, several linear models will be constructed in this section: one univariate model and three multivariate models concerned with the effect of knowledge claims across party families, whether or not a tweet is original, i.e. not a retweet on an existing tweet, and UK vs other EU MP origin countries. The linear regression models below provide a rather simplistic but straightforward approach to estimating the effect of knowledge claims on retweet count, as the models do not account for who retweeted something —individuals, organisations, politicians, or fake Twitter accounts, i.e. bots (Marres & Moats, 2015) — and does not consider the sentiment of a given retweet (negative or positive). The following section will discuss the applied method.

3.5.1 Power-Law Distribution

Schelling (2006) points out that tipping points lead to instability. Figure 2.3 shows an instability between equilibriums, inactivity at first, followed by a flood of activity (Margetts et al., 2016). In narratives initiated via social media messaging, Schelling's (2006) 'number expected to attend' (see fig. 2.3) will be informed by the retweet count shown to the user beneath each tweet, that is, an indication of the number of individuals already transported by the tweet. Schelling (2006) assumes that people can guess the 'number expected,' however, with the precise information available to the user beneath each tweet, it may be possible to test this assumption with the available Twitter data (Margetts et al., 2016).

In case of the existence of tipping points and disruptive diffusion of some tweets, it should be expected that the distribution of retweet count within the data set does not follow a random distribution. If each tweet was assigned a random retweet count, a normal distribution could be expected. However, this should not be the case. As shown in fig. 3.7, the data set considered for this study shows a power-law distribution. Figure 3.7 shows bins of tweets. Each bin has been assigned a number of tweets according to their share of the total retweet count (x) in the data set. Bin one has been assigned all tweets in the first percentile, and bin two contains all tweets between the first and second percentile, and so on. This way, 100 bins are created. Each bin (b) is associated with a size equal to the count of all tweets contained within it (n_b) and a weight equal to the average retweet count ($x_b / \sum_{b=1}^{100} x_b$) of observed tweets within the bin.

The power law states that a change in one quantity results in a proportional change in another (Raban & Rabin, 2009). So, for example, if one doubles the length of one side of a square, then the area will quadruple (see eq. 3.1).

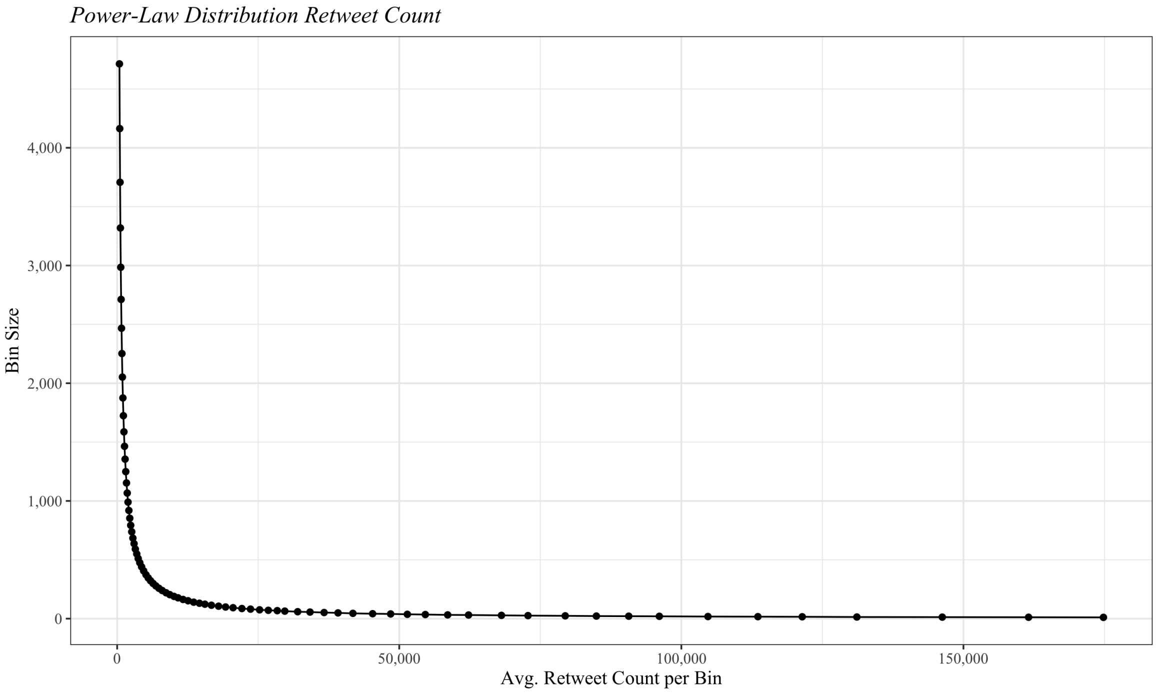

Figure 3.7: Distribution of retweet count.

$$p(x) = ax^{-\alpha} \tag{3.1}$$

When x stands for the retweet count of a given tweet, then the probability of measuring x varies inversely as a power of x (Raban & Rabin, 2009). According to Raban & Rabin (2009), the formula (eq. 3.1) indicates that the probability of large events is very small, and the probability of small events is high. As shown in fig. 3.7, this is true for the distribution of the retweet counts observed in the data set.

Raban and Rabin point out that “power law distributions of social networks are typically attributed to a process called preferential attachment or positive feedback whereby new entrants will prefer to link or attach to ‘winners’ resulting in a small number of nodes with a large number of links and a large number of nodes with a small number of links” (Barabasi and Albert, 1999; Shapiro and Varian, 1999. Cited after Raban & Rabin, 2009, p. 268). This phenomenon strengthens the proposed participation threshold and tipping point argument discussed above (Granovetter &

Soong, 1983; Margetts et al., 2016; Schelling, 2006). Assuming that users see each tweet in the context of its diffusion, i.e. success among other users, they are more likely to participate in its diffusion, also — in other words, attach to 'winners' (Raban & Rabin, 2009, p. 268).

According to Raban & Rabin (2009, p. 268), power-law distributions are detected by plotting data on the logarithmic scale, which equals taking the logarithm from both variables, x and $p(x)$. A power-law distribution is indicated by a straight line on the plot. The slope of the line is equal to the exponent, a.

$$\ln(p(x)) = -\alpha \ln(x) + \ln(a) \tag{3.2}$$

Thus, to confirm that the retweet count in the data follows a power-law distribution, the retweet count variable is plotted on the logarithmic scale (fig. 3.8).

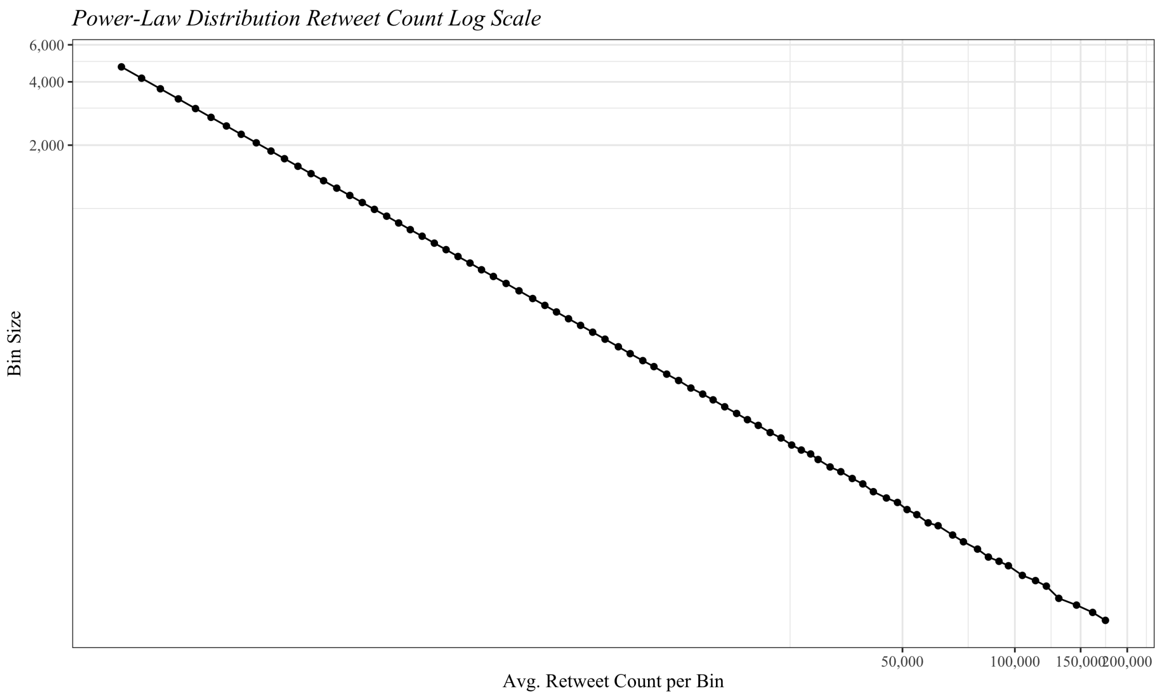

Figure 3.8: Distribution of retweet count on the logarithmic scale.

The linear relationship shown in fig. 3.8 suggests that retweet count x and n have a proportional relationship. It is thus argued that the retweet count follows a power-law distribution. To identify whether covariates follow a similar distribution, the same procedure has been applied to *status count, friend count, and follower count* (fig. 3.9)

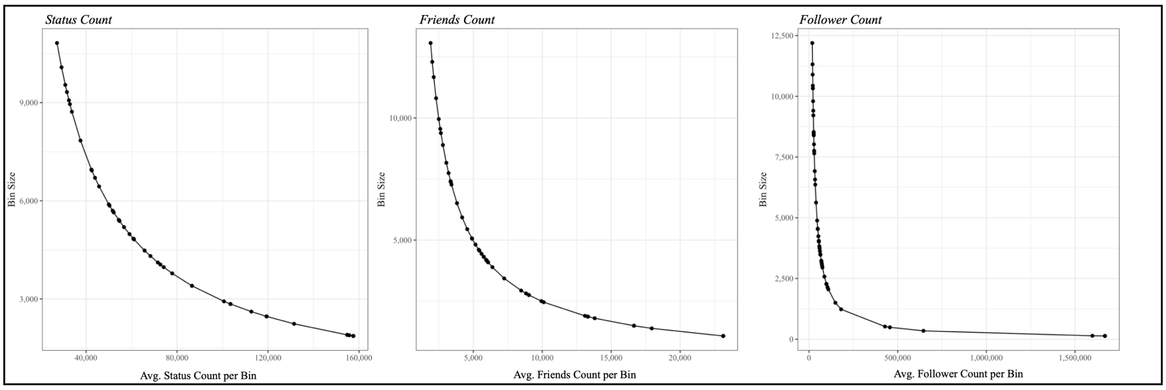

Figure 3.9: Distribution of status count, friends count, and follower count.

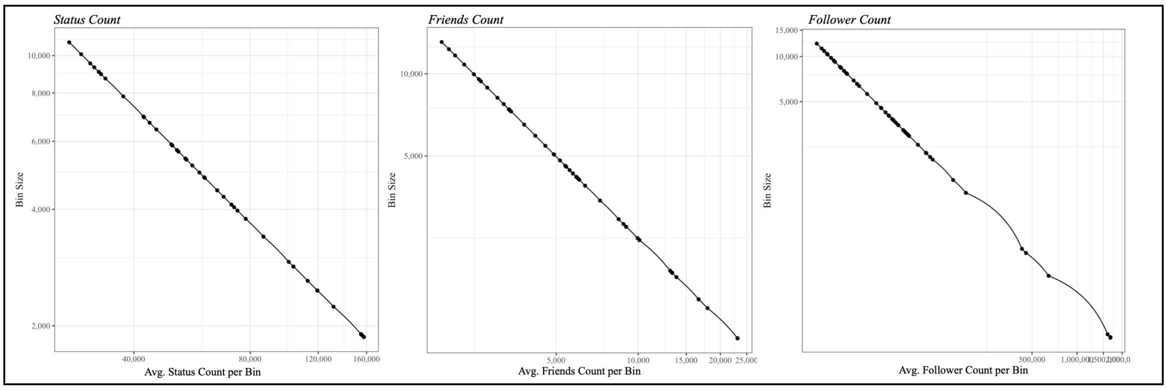

Figure 3.10: Distribution of status count, friends count, and follower count on the logarithmic scale.

As fig. 3.10 shows, all three covariates follow a power-law distribution. These findings will be essential in choosing the proper method when applying the linear regression models below. This paper will apply the method proposed by Raban & Rabin (2009) to apply a logarithmic transformation to all variables and covariates that follow a power-law distribution before running a linear regression model. Raban & Rabin (2009) confirmed the robustness of their models by plotting a histogram of the residuals of their models (see section 4.1)

3.5.2 Linear Models

This thesis will apply several linear regression models to estimate the effect of knowledge claims on the diffusion of narratives. The following paragraphs will present the constructed models and explain their logic regarding the previous discussion of theory and explorative analysis. The preceding sections have identified biases, defined the sample population, and applied further measures to limit variation. This section aims to present a set of equations that utilise the discussion above and explain the remaining variation of retweet count in the dataset.

$$y_1 = \beta_0 + \beta_1 + \beta_2 exknow + e \tag{3.3}$$

The univariate regression model (eq. 3.3) estimates the effect of the independent variable 'knowledge claims' ($exknow$) on the dependent variable retweet count (y). The knowledge claim variable is a dummy variable, consisting of a value of 0 when a tweet did not contain a knowledge claim and 1 when it did. The purpose of the univariate model is to give a first impression of the effect of knowledge claims. However, as the correlation of y with the error term (e) is expected to be too high to provide a sufficient understanding of the effect of the independent variable, it is necessary to provide a model considering controlling variables.

$$\begin{aligned} y_2 = \beta_0 + \beta_1 exknow + \beta_2 followers \\ + \beta_3 statuses + \beta_4 friends + e \end{aligned} \tag{3.4}$$

The multivariate model eq. 3.4 estimates the effect of knowledge claims on retweet count, like eq. 3.3, while also controlling for follower count ($followers$), status count ($statuses$), and friends count ($friends$). These covariates have been selected to account for any effects they might have on the retweet count. As discussed above, the number of followers and friends a user has indicates the degree centrality of the user in the Twitter network (Ma et al., 2018). The degree centrality is an essential measure of a user's impact on other users in the network (Ma et al., 2018). As this thesis is interested in how the EP impacts the network and not how actors are impacted by the network, a variable that indicates the count of users the EP follows, i.e. the in-degree, can be omitted without any concern. While friends count can give some insight into in-degree, the focus should lie on the out-degree, i.e. how many other users the EP can reach in their local network. Additionally, a measure of how many users the EP follows is not provided by the available Twitter data.

$$\begin{aligned} \ln(y_3) = \beta_0 + \beta_1 exknow + \beta_2 \ln(followers) \\ + \beta_3 \ln(statuses) + \beta_4 \ln(friends) + e \end{aligned} \tag{3.5}$$

As a result of the discussion in section 3.5.1 and suggested by Raban & Rabin (2009), **??** applies a logarithmic transformation to the dependent variable, and all right-skewed covariates — $followers$, $statuses$, and $friends$. This is expected to normalise the power-law distribution found within the data and increase the model's performance. For the interpretation of the results, this has several implications. Firstly, all coefficients of logged covariates should be interpreted as a per cent increase in the dependent variable for every 1% increase in the independent variable (Ford, 2018). Secondly, the exponentiated coefficient $((e^{\beta_1} - 1) * 100)$ of the independent variable *knowledge claim* is interpreted as the percentage increase of the dependent variable (Ford, 2018).

$$\begin{aligned} \ln(y_4) = \beta_0 &+ \beta_1 exknow + \beta_2 \ln(followers) + \beta_3 \ln(statuses) + \beta_4 \ln(friends) \\ &+ \beta_5 radicalTAN + \beta_6 cons + \beta_7 lib + \beta_8 chrDem + \beta_9 social \\ &+ \beta_{10} radLeft + \beta_{11} green + \beta_{12} regio + \beta_{13} confessional + e \end{aligned} \tag{3.6}$$

The third and final model (eq. 3.6) applied in this thesis leverages eq. 3.5 and examines knowledge claims and retweet count in the context of EP party family affiliation. This model makes use of the party family categories identified by the CHES. The CHES measured EPs across ten categories of party families: Radical right ($radicalTAN$), conservative ($cons$), liberal (lib), christian democratic ($chrDem$), social-democratic ($social$), radical left ($radLeft$), green ($green$), regionalist ($regio$), and lastly confessional ($confessional$). Those observations that do not fit any category according to the CHES (see Polk et al., 2017) have been left out of eq. 3.6 to provide a simpler model. As it is not clear who is in this category, it is not expected to contribute structurally to the model. To deal with the categorical CHES variable, dummy variables have been constructed for each category. These dummies have the value 1 whenever the category is observed. Additionally, all-controlling variables from the previous two multivariate models have been applied as controlling variables. The interpretation follows the one of eq. 3.5. All categorical, untransformed variables should be plugged into the formula $(e^{\beta} - 1) * 100$ to make the results comparable. This regression is expected to give additional insights into how knowledge claims affect the diffusion of EP tweets as it considers all-controlling variables and adds the perspective of party families.

Chapter 4

Results

This chapter will present the results of the linear models described above. By discussing the empirical evidence in the context of the theoretical framework, this section aims to provide the basis for the conclusion and the assessment of the hypotheses and research question.

4.1 Regression Findings

Table 4.1 compares two linear models, the univariate model (4.1.1, eq. 3.3) and the multivariate model (4.1.2 - 4, eq. 3.4). Table 4.1 shows OLS regressions on the untransformed data, which will be compared to the results of the log-transformed data in table 4.2. The models were applied to the entire data set of 583,780 observations. When comparing the knowledge claim variable (exknow) to the constant, it appears that the presence of knowledge claims has had an overall negative effect on retweet count across all models. The controlling variables 'user_follower_count,' 'user_statuses_count,' and 'user_friends_count' offer no insights. Even though the results here are significant, paired with a small standard deviation, the effects are too small to produce any observable differences. In the case of 'user_followers_count' variable, the interpretation is as follows: as the number of followers on an EP increases by 1, retweet count increases by 0.001. In cases where an EP shows a very high follower count, as is the case with Marine Le Pen (2,553,857 followers), the effect may result in a meaningful difference — Marine Le Pen, on average, gains around 2,553 retweets solely due to her large follower count. However, as the effect presented in table 4.1 is rounded up from around 0.000002 (with an even lower standard deviation), the effect can not be interpreted as meaningful — Marie Le Pen would only profit from her follower count by five retweets. The same is true for friends and the status count of an EP.

All models presented in table 4.1 show minimal R2 values, meaning that these models are suspected only to explain a small percentage of the total variance in the data. As pointed out by Raban & Rabin (2009), a common problem with right-skewed data, such as power-law distributed data, is the overall very low p-values paired with very low R-squared values. While low p-values point to statistically significant coefficients, low R-squared values point to high variance in the data. For OLS regressions, this means that the model produces significant coefficients, while the data points lie far away from the fitted regression line. This is contradictory and does not indicate a robust model. Even though R2 is not the perfect measurement of model performance (Berry and Feldman 1985; King 1986) and is not expected to perform perfectly on data that shows a great deal of variation in general, the following models shall attempt to increase the R2 value.

To deal with the challenges of the power-law distribution, the data has been transformed with the natural logarithm, as suggested by Raban & Rabin (2009). Results are shown in table 4.2. After normalizing the data, table 4.2 shows much more promising p-values and R-squared measurements. Although statistical significance still seems to be very high, especially in model 4.2.4, p-values are overall very low. This is expected to be the result of applying large amounts of data (see Raban &

Table 4.1: Regression of Knowledge Claims on Retweet Count

	Dependent Variable			
	Retweet Count			
	Model 4.1.1	Model 4.1.2	Model 4.1.3	Model 4.1.4
exknow	−85.135***	−81.785***	−82.853***	−82.571***
	(30.656)	(30.653)	(30.657)	(30.660)
user_followers_count		0.001***	0.001***	0.001***
		(0.0001)	(0.0001)	(0.0001)
user_statuses_count			−0.0003**	−0.0003**
			(0.0001)	(0.0001)
user_friends_count				0.001
				(0.001)
Constant	330.426***	306.008***	319.647***	317.059***
	(6.441)	(6.737)	(9.466)	(10.151)
Observations	583,780	583,780	583,780	583,780
R^2	0.00001	0.0003	0.0003	0.0003
Adjusted R^2	0.00001	0.0003	0.0003	0.0003
Residual Std. Error	4,811.535 (df=583778)	4,810.912 (df=583777)	4,810.898 (df=583776)	4,810.900 (df=583775)
F Statistic	7.712*** (df=1; 583778)	79.985*** (df=2; 583777)	54.726*** (df=3; 583776)	41.169*** (df=4; 583775)

Note: *p<0.1; **p<0.05; ***p<0.01
Linear regression on the untransformed data set. Model 4.1.1: Univariate model on the data (eq. 3.3); Model 4.1.4: Multivariate model (eq. 3.4). To monitor each variables effect on the dependent variable, Model 4.1.2 - Model 4.1.4 introduce each covariate step by step.

Rabin, 2009). However, the univariate model 4.2.1 no longer shows a high statistical significance for the knowledge claim variable gives confidence about the increased quality of the regression analysis because it is not expected that knowledge claims alone can explain much variance in the data. Additionally, the R-squared values have increased, from 0.03% in model 4.1.4 to 3.4% in model 4.2.4, which indicates that the data points lie closer to the fitted regression line (see fig. 4.1). Figure 4.1 shows that the logarithm could draw out most of the observations and, thus, reveal the effect of the independent on the dependent variable.

Models 4.2.1 - 4 (table 4.2) were aligned in a way that shows the introduction of the controlling variables one by one to observe the individual effects on the dependent variable and the model's performance. While the performance of the multivariate models increases substantially between model 4.2.1 - 3, model 4.2.4 does not increase the performance by a lot. Neither does the introduction of friends

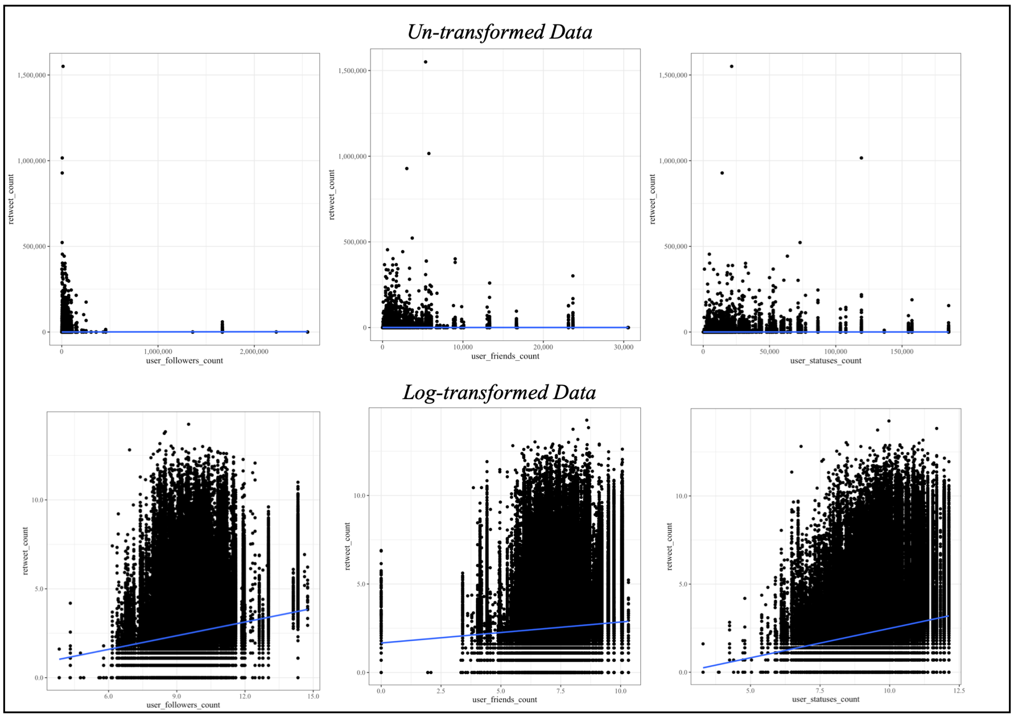

Figure 4.1: Fitted regression of covariates on retweet count before and after transformation.

count affect the knowledge claim coefficient much. Compared to model 4.2.1 - 3, model 4.2.4 appears to arrive at a statistically significant measure of 0.046 with a standard error of 0.014. This is interpreted as a change of 4.71% $((e^{0.046} - 1) * 100)$ in retweet count when the effect of knowledge claims is present (see Ford, 2018). The effects of follower count and status count are both positive and interpreted as an increase of the dependent variable by 0.135% per 1% increase in follower count, or 0.304% increase in 1% increase of status count.

On the other hand, the friends count decreases retweet count by 0.04% per 1% increase of friends count. Considering these results, friends count does not contribute much explanation to the model and could be omitted. The variables that provide the most explanatory power are user follower count, as an indicator of the out-degree of the EP, and user statuses count as an indicator for the activity of the EP. Model 4.2.4 can show a small, yet significant, positive effect of knowledge claims on retweet count. The following regression analyses will apply model 4.2.4 to different subsets

Table 4.2: Regression of Knowledge Claims on Retweet Count *(log transformed)*

	Dependent Variable			
	Retweet Count			
	Model 4.2.1	Model 4.2.2	Model 4.2.3	Model 4.2.4
exknow	0.018	0.021	0.048***	0.046***
	(0.014)	(0.014)	(0.014)	(0.014)
user_followers_count		0.257***	0.132***	0.135***
		(0.003)	(0.003)	(0.003)
user_statuses_count			0.288***	0.304***
			(0.003)	(0.003)
user_friends_count				−0.040***
				(0.003)
Constant	2.585***	0.053*	−1.684***	−1.571***
	(0.003)	(0.028)	(0.032)	(0.033)
Observations	583,780	583,780	583,780	583,780
R^2	0.00000	0.014	0.034	0.034
Adjusted R^2	0.00000	0.014	0.034	0.034
Residual Std. Error	2.220	2.203	2.182	2.182
	(df=583778)	(df=583777)	(df=583776)	(df=583775)
F Statistic	1.557	4,266.162***	6,760.389***	5,124.791***
	(df=1; 583778)	(df=2; 583777)	(df=3; 583776)	(df=4; 583775)

Note: *p<0.1; **p<0.05; ***p<0.01
Linear regression on the data set, transformed by the natural logarithm. Model 4.2.1: Log-transformed univariate model on the data (eq. 3.3). Model 4.2.4: Multivariate model (eq. 3.5). To monitor each variable's effect on the dependent variable, Model 4.2.1 - Model 4.2.4 introduce each covariate step by step.

of the data. These subsets have been selected bases on the previous discussion and explorative analysis to shed more light on the observed effects.

Firstly, the multivariate model (**??**) shall be rerun on those observations that are original tweets. Excluding retweets also has the advantage that the focus will be on tweets at the beginning of the narrative diffusion process. These tweets are not viewed in the context of other tweets and are therefore not directly influenced by them. For comparison, this thesis presents the same model regressed on the remaining data, containing retweets only. This will be done to detect differences in the way political actors communicate on Twitter. For example, if an EP responds to another EP or other users, characteristics specific to this third party may affect user engagement with the tweet. Therefore, in the case of an EP retweeting, it is not possible to know how far the diffusion of this tweet is due to the rhetoric of the EP compared to the contents of the original tweet.

Table 4.3: Knowledge Claims in Retweets

	Dependent Variable		
	Retweet Count		
	Model 4.3.1	Model 4.3.2	Model 4.3.3
exknow	0.046***	0.205***	−0.133***
	(0.014)	(0.016)	(0.017)
user_followers_count	0.135***	0.817***	0.055***
	(0.003)	(0.003)	(0.004)
user_statuses_count	0.304***	−0.270***	0.244***
	(0.003)	(0.003)	(0.004)
user_friends_count	−0.040***	−0.078***	0.028***
	(0.003)	(0.003)	(0.004)
Constant	−1.571***	−3.519***	0.148***
	(0.033)	(0.035)	(0.042)
Observations	583,780	239,470	344,310
R^2	0.034	0.194	0.023
Adjusted R^2	0.034	0.194	0.023
Residual Std. Error	2.182 (df=583775)	1.536 (df=239465)	2.097 (df=344305)
F Statistic	5,124.791*** (df=4; 583775)	14,441.490*** (df=4; 239465)	2,053.179*** (df=4; 344305)

Note: *p<0.1; **p<0.05; ***p<0.01
Model 4.3.1: Multivariate model (eq. 3.5) on entire dataset (same as in tab. 4.2 for comparison). Model 4.3.2: Multivariate model (eq. 3.5), no retweets. Model 4.3.3: Multivariate model (eq. 3.5), only retweets.

Considering the independent variable 'exknow' in model 4.3.2, it appears that the effect of knowledge claims on retweet count has increased from about 4% to 20% and remained positive. At the same time, the standard deviation remained roughly the same. However, compared to the increased strength of the effect, the standard deviation has a smaller impact on the measured effect. The constant of model 4.3.2 decreased from -1.571 in model 4.2.4 to -3.519, which may be due to the lower average in retweet count among original tweets in the data set (see table 3.1). The R-squared value of model 4.3.2 is the highest so far and reaches nearly 20%.

Regression 4.3.3 looks at only retweets and contrasts model 4.3.2 in that knowledge claims here have an overall negative effect. Knowledge claims are observed to decrease retweet count by 13.3%. However, compared to model 4.3.2., the R-squared performance of regression 4.3.3 is weaker.

Lastly, the explanatory scope of the multivariate model (eq. 3.6) will be widened by including variables concerned with EP party family in the model. As shown in fig. 3.2 the UK EPs make up a large part of the sample. Therefore, the characteristics of UK EPs are expected to distort the measurements, particularly regarding the party family measurements. However, leaving the UK entirely out of the picture is not the best solution, as the UK is an EU member during the timeframe of this study (September 2017 to April 2019) and is, therefore, part of the explanation this thesis aims for. The best strategy to deal with the UK overrepresentation bias in the data is to compare different models that either leave the UK out or focus on the UK only. Thus, it is possible to identify differences and account for the bias discoursively.

Table 4.4 shows the results of eq. 3.6 while considering different data selections in each column. Regression 4.3.1 shows results regarding all observations that contain information about the party family affiliation. All other observations are left out to avoid false negatives — EPs affiliated to a party family but not considered by the CHES. Building on the previous model and the findings of table 4.3 model 4.4.2 leaves out retweets in addition to observations that lie outside the scope of the CHES. Model 4.4.3 ignores UK EPs, which are expected to pose a bias concerning CHES party family observations, as the vast majority of UK EPs in the data set are associated with the 'radicalTAN' family. Lastly, model 4.4.4 and model 4.4.5 separate model 4.4.3 by knowledge claims. Model 4.4.4 contains only knowledge claims, while model 4.4.5 contains none.

As expected from the preceding regressions, considering retweets and original tweets produces a statistically significant small positive effect of knowledge claims on the dependent variable. This effect gets more significant, and the standard error decreases the more the data gets distilled along each model in table 4.4. The effects vary across all models in terms of the controlling variables, followers, statuses, and friends. The most variation can be found in the friends variable. Here, the coefficients change from negative to positive and model 4.4.4 can not produce a significant coefficient.

The following paragraphs will discuss the measured effects of party families in table 4.4. Instead of explaining each coefficient, the discussion will focus on the most compelling measurements. While model 4.4.1 - 3 apply each party family category to the data without considering expert knowledge, model 4.4.4 - 5 apply the knowledge claim variable as a reference category. This will enable a comparison of the effect of knowledge claims on retweet count across party categories.

All party families, except right-wing and liberal, are associated with a significant effect across all models, everything else being equal. According to table 4.4, right-wing parties positively affect retweet count, while liberal parties have a negative effect. Conservatives also have a negative effect. However, this effect is only significant for model 4.4.1 - 2. The negative effect cannot be falsified by a significantly positive measurement, so it is fair to assume that the effect is overall negative. Similarly, for social democrats, there are only statistically significant negative measurements found in table 4.4. All other party families show contradictory results across model 4.4.1 - 3.

As model 4.4.3 is the furthest distilled model and expected to provide the most comprehensive understanding of how party families affect retweet count, the following paragraph will describe the results of this model according to the expert knowledge reference category (model 4.4.4 - 5). Firstly, the constant shows that tweets that contain knowledge claims have a higher average retweet count than those that do not, at least given that each variable in the model is equal to zero. This finding can be confirmed by the results shown in table 4.3, where knowledge claims are associated with a positive effect on retweet count or original tweets. In all cases, except regionalists and confessionals, it appears that retweet count remains positive or negative according to the results of model 4.4.3. Only for regionalists, both measures are significant. This points to the argument that party family has a stronger effect on the retweet count than knowledge claims.

It appears that in each case where there is a statistically significant measurement, the knowledge claim data set produces a slightly higher effect in the party family variable, except for the case of regionalists. However, the 'regio' category does not have much explanatory power, despite being significant. Only 3 EPs were observed in model 4.4.3 (Herbert Dorfmann, Lorenzo Fontana, and Matteo Salvini), contributing 161 tweets. The observed effect could be largely random and associated with the EPs themselves rather than the party family.

In terms of the overall performance of the five regressions, it can be said that 4.3.2 - 5 provide the most explanation of the variance in the data. With model 4.4.3 having the highest R2. The R2 show that the models can account for roughly 30% of the total variance in the data. Again, it should be noted that R2 is not a flawless measurement of model performance (Berry and Feldman 1985; King 1986).

Table 4.4: Chapel Hill Expert Survey Party Families

	Dependent Variable				
	Retweet Count				
	Model 4.4.1	Model 4.4.2	Model 4.4.3	Model 4.4.4	Model 4.4.5
exknow	0.014	0.088**	0.095***		
	(0.025)	(0.034)	(0.033)		
user_followers_count	0.020***	0.772***	0.370***	0.432***	0.360***
	(0.004)	(0.005)	(0.010)	(0.044)	(0.010)
user_statuses_count	0.285***	−0.256***	−0.327***	−0.372***	−0.320***
	(0.006)	(0.006)	(0.010)	(0.039)	(0.010)
user_friends_count	−0.113***	−0.233***	0.082***	0.014	0.084***
	(0.005)	(0.005)	(0.011)	(0.052)	(0.011)
radicalTAN	0.113***	0.526***	1.045***	1.277***	1.057***
	(0.033)	(0.042)	(0.065)	(0.418)	(0.066)
cons	−0.598***	−0.523***	−0.058	−0.350	−0.035
	(0.050)	(0.059)	(0.044)	(0.214)	(0.045)
lib	−0.512***	−0.573***	−0.373***	−1.044***	−0.340***
	(0.064)	(0.082)	(0.059)	(0.319)	(0.060)
chrDem	−0.933***	0.029	0.518***	0.078	0.555***
	(0.036)	(0.046)	(0.035)	(0.144)	(0.036)
social	−0.166***	−0.205***	0.044	0.070	0.048
	(0.035)	(0.044)	(0.033)	(0.130)	(0.034)
radLeft	−0.158**	0.570***	0.881***	0.460	0.907***
	(0.062)	(0.094)	(0.069)	(0.318)	(0.070)
green	−0.212***	0.442***	0.362***	0.612***	0.348***
	(0.047)	(0.058)	(0.043)	(0.168)	(0.044)
regio	0.557***	1.339***	1.184***	−0.618*	1.336***
	(0.047)	(0.051)	(0.097)	(0.344)	(0.101)
confessional	−0.555***	0.240***	0.258***	−0.045	0.280***
	(0.042)	(0.061)	(0.044)	(0.165)	(0.046)
Constant	0.480***	−2.434***	−0.281***	0.315	−0.291***
	(0.065)	(0.076)	(0.085)	(0.364)	(0.087)
Observations	209,114	68,984	20,273	1,273	19,000
R^2	0.044	0.292	0.146	0.163	0.149
Adjusted R^2	0.044	0.292	0.145	0.155	0.148
Residual Std. Error	2.182 (df=209100)	1.566 (df=68970)	1.120 (df=20259)	1.061 (df=1260)	1.121 (df=18987)
F Statistic	748.136*** (df=13; 209100)	2,192.170*** (df=13; 68970)	265.406*** (df=13; 20259)	20.505*** (df=12; 1260)	276.537*** (df=12; 18987)

Note: *p<0.1; **p<0.05; ***p<0.01
These regressions all use the multivariate CHES model (eq. 3.6). Model 4.4.1: Regression on the entire data set. Model 4.4.2: Regression on only original tweets. Model 4.4.3: Regression on only original tweets, disregardingUK EPs. Model 4.4.4: Regression on only original tweets, disregarding UK EPs and non knowledge claim tweets. Model 4.4.5: Regression on only original tweets, disregarding UK EPs and knowledge claim tweets.

Including the party family dimension does not provide much explanatory power to the effect of expert knowledge on retweet count. It seems to complicate the discussion unnecessarily. The available data does not seem to be sufficient to explain the differences between party families along the knowledge claim dimension. In most cases, only one significant effect could be measured, for either exknow = 1 or exknow = 2. That makes comparison difficult.

Additionally, after examining the results of table 4.4 it appears, that the model with the most explanatory power is model 4.4.2 (original tweets only), according to its R2 value. Excluding the UK does no lead to an increase in performance. Neither does leaving out knowledge claims in model 4.4.4 or focusing on knowledge claims only in model 4.4.5. Thus, the following discussion will disregard the findings of table 4.4.

4.2 Robustness Checks

To conclude chapter 4 this study will consider several methods to check for the robustness of the applied models. Firstly, the distribution of residuals shall be examined. Secondly, this section tests for multicollinearity.

4.2.1 Distribution of Residuals

Figure 4.2 shows the distribution of residuals by frequency. To better visualise the distribution, residuals have been collected into ten bins per model. As fig. 4.2 shows, the residuals of model 4.1.4 are right-skewed and not normally distributed. According to Raban & Rabin (2009), this points toward a less robust model. Model 4.1.4 (see table 4.1) was applied to the untransformed data, which shows that a linear regression on power-law distributed data does not produce the best results. As discussed above, Raban & Rabin (2009) suggest applying the natural logarithm to power-law distributed data to make it accessible to linear regression models. The second histogram in fig. 4.2 shows the residuals after transforming retweet count, follower count, status count, and friends count with the natural logarithm (model 4.2.4). Here, the residuals are much more normally distributed, pointing towards a much more robust approach to handling the data (Raban & Rabin, 2009).

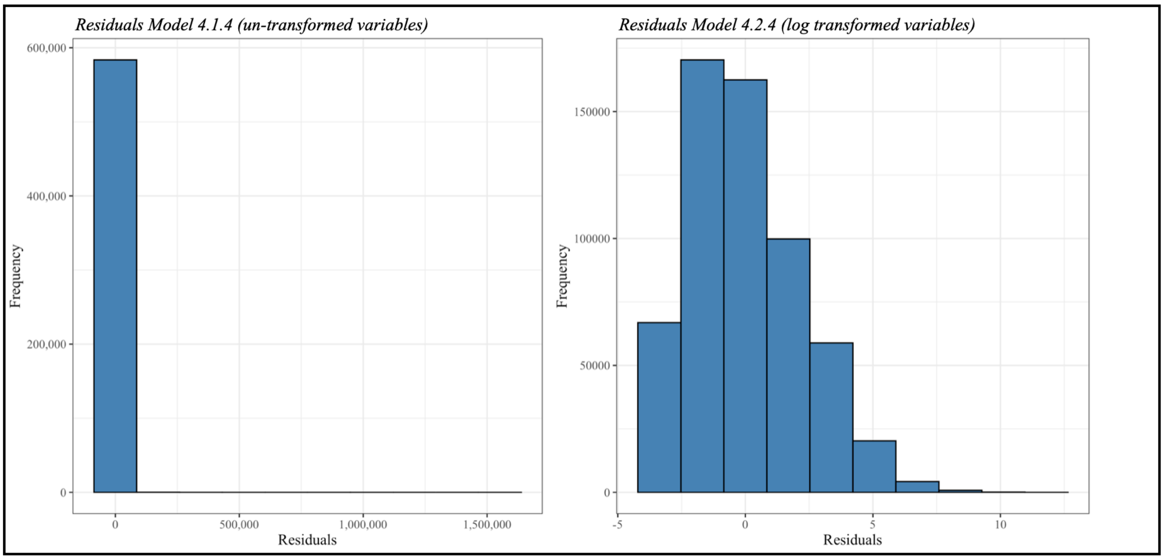

Figure 4.2: Histogram of the residuals of Model 5.1.4 and Model 5.2.4.

4.2.2 Multicollinearity Tests

In addition to checking the distribution of residuals visually above, this study investigates multicollinearity by constructing two correlation matrixes and applying a method designed to measure multicollinearity in linear models (see Fox, Weisberg, & Price, 2020). Table 4.5 shows the correlation matrix of the untransformed data, and table 4.6 shows the correlation matrix of the transformed data.

Table 4.5: Correlation matrix.

	retweet_count	exknow	user_followers_count	user_friends_count	user_statuses_count
retweet_count	1				
exknow	-0.00363	1			
user_followers_count	0.01618	-0.00886	1		
user_friends_count	-0.00026	-0.01655	-0.03318	1	
user_statuses_count	-0.00287	-0.01684	-0.01523	0.25104	1

Table 4.6: Correlation matrix transformed with natural logarithm.

	retweet_count	exknow	user_followers_count	user_friends_count	user_statuses_count
retweet_count	1				
exknow	0.00163	1			
user_followers_count	0.12001	-0.00285	1		
user_friends_count	0.0618	-0.01987	0.2222	1	
user_statuses_count	0.1741	-0.01772	0.38769	0.43242	1

In both cases, there appears to be no multicollinearity. As shown in table 4.6, there are no high correlations between the independent variables. *Friends count* and *followers count* show a slightly elevated correlation with *status count*. This seems logical since more active users probably have more connections on Twitter, both friends and followers. However, the correlation is not high enough to point to multicollinearity. It could be argued that the model can be made simpler by excluding status count. However, as the model is straightforward as is, and the status count measure is the only indicator for activity, it is suggested to include status count rather than remove it.

Table 4.7: Variance Inflation Factor.

	Variance Inflation Factor
	Untransformed
exknow	1.00
user_followers_count	1.00
user_statuses_count	1.07
user_friends_count	1.07
	Transformed by Natural Log.
exknow	1.00
user_followers_count	1.18
user_statuses_count	1.38
user_friends_count	1.24

More confidence about the applied linear model can be drawn from the variance inflation factor in table 4.7. The variance inflation factor provides an index to linear regression analysis, which indicates how much the variance of a regression coefficient increases due to collinearity (Fox et al., 2020; see Kutner, Nachtsheim, Neter, & Li, 2005). A variance inflation factor below ten indicates the absence of collinearity (Kutner et al., 2005). Table 4.7 shows that in both the transformed and untransformed data, there are no variables with a variance inflation factor of higher than 1.3, which shows that there is no collinearity that could affect the robustness of the model. Additionally, the variance inflation factor provides further confidence in leaving the status count covariate in the model to explain the dependent variable retweet count better.

4.3 Analysis

The regression analysis above produces four major insights.

1. Party families provide no additional insights into the effect of knowledge claims on retweet count.
2. The data shows very few tweets with a lot of retweets and a lot of tweets with very few retweets. This phenomenon points toward a power-law distribution and the presence of thresholds and tipping points in the way tweets diffuse (Granovetter & Soong, 1983; Margetts et al., 2016; see Schelling, 2006).
3. Overall, knowledge claims have a positive effect on the diffusion of EP tweets.
4. Narrative initiating tweets (original tweets) lead to a greater diffusion, and narrative challenging tweets (retweets) negatively affect diffusion.

The effect of knowledge claims on retweet count is shown to be negative in the case of retweets. Retweets of EPs are seen as reactions to already diffused narratives. This means that knowledge claims in retweets are perceived in the context of these narratives. Boswell et al. (2011) point out that political actors often utilize knowledge claims to engage in competition. If this assumption holds for the sample scrutinized by the linear models, it can be argued that knowledge claims that are applied in response to already diffused narratives are applied with a different aim than knowledge claims in the context of original tweets. Tweets responding to other tweets are considered either a positive or negative response to an existing narrative. Considering the Boswell et al. (2011) argument of competitive use of knowledge claims in narratives, it can be argued that knowledge claims in retweets are often used competitively and are, therefore, narrative challenging.

An EP may attempt to disprove the preceding arguments by deploying knowledge claims. According to Boswell et al. (2011), this produces mistrust among individuals as it leads to contradictory knowledge claims. One actor may claim (A) to be true based on evidence, while another actor claims (A) to be invalid based on other evidence. This mistrust is seen as a possible explanation of the negative effect of knowledge claims among retweets (see model 4.3.3).

The negative effect of mistrust on persuasiveness is also supported by the 'narrator trust' variable, put forth by Jones & McBeth (2010). According to Jones & McBeth (2010), narrator trust affects the persuasiveness of narratives. EPs that are perceived as trustworthy are expected to construct more persuasive narratives than those that are perceived to be not trustworthy. Accordingly, this thesis argues that knowledge claims in retweets show a negative effect on retweet count due to a lack of trust on the part of the competitive use of knowledge claims in reaction to existing narratives.

Original tweets, on the other hand, deploy narratives with a different aim in mind. Roe points out that narratives provide "the assumptions needed for decision-making in the face of what is genuinely uncertain and complex" Boswell (2008). In the face of uncertainty, narratives enable actors and individuals to grasp and communicate who should do what, how, when, and why (Boswell, 2008). As a result, narratives generate support by establishing a coherent account of complicated phenomena [see Ricoeur 1984; Banerjee,1998]. In this context, EPs utilize knowledge claims to provide minimum cognitive requirements to the formulated narratives and validate them (Boswell et al., 2011).

Here, the narrative stands at the beginning of the diffusion process and introduces a new discussion, i.e. narrative initiating. In this context, the positive effect of knowledge claims on retweet count point toward the better performance of narratives with knowledge claims compared to those without knowledge claims. Therefore, it can be said that, outside of a competitive context, anchoring narratives in empirical evidence has a positive effect on the degree of diffusion.

The contrast of the competitive and the validating use of knowledge claims in narratives in social media messaging can also be interpreted in the context of Jasanoff's (2004) concept of co-production of science and policy. On the one hand, political actors rely on the use of evidence, data, and science to navigate an increasingly complex and uncertain world — with a growing congruence of data and evidence on the part of the public, actors are even expected to provide empirically grounded narratives (Boswell et al., 2011). On the other hand, the public views knowledge claims increasingly sceptically, which creates mistrust (see Jones & McBeth, 2010). This is to say that the competitive use of knowledge claims in narratives on Twitter generates mistrust, while the validating use of knowledge claims appears to have the opposite effect and increase the persuasiveness of a given narrative.

Finding three relates to the discussion surrounding thresholds and tipping points found in collective behaviour (see Granovetter & Soong, 1983; Margetts et al., 2016; Schelling, 2006). The complex distribution of retweet count, status count, friends count, and follower count provides several challenges to which there has no 'one fits all' solution been found yet (Ma et al., 2018; Raban & Rabin, 2009). However, the circumstance that users can at any point monitor the number of retweets a tweet received, i.e. the degree of diffusion, provides the ability to discuss the participation threshold more concretely (Margetts et al., 2016). The power-law distribution found in the data point toward a threshold that needs to be overcome before tweets can diffuse rapidly. Most tweets are shown to have very few retweets, while few tweets are associated with large retweet counts. Thus, the behaviour of retweet count seems systemic and not random. Assuming that the mechanism at play is the participation threshold, the following argument is plausible.

As discussed in chapter 2, knowledge claims affect the persuasiveness of narratives, persuasiveness affects an individuals threshold to being transported by the narrative, each transported individual raises the degree of diffusion, the greater the diffusion, the more individuals have a threshold lower than the degree of diffusion. Considering this conceptualization, the following argument is reached. Knowledge claims only affect the diffusion of a narrative as long as the retweet count is below the tipping point. Once retweet count grows beyond the threshold of most individuals in the network, it surpasses the tipping point and persuasiveness, which is affected by knowledge claims, ceases to matter to the diffusion of the tweet. Thus, given that the participation threshold is a relevant mechanism in the diffusion process, which seems to be the case, considering the results of this study and the scientific literature, knowledge claims only play a role while diffusion is below the tipping point. While knowledge claims seem less effective at increasing the diffusion of narrative challenging tweets, they are a vital tool for narrative initiating tweets and help to bring them past the tipping point.

4.3.1 Hypotheses

Based on the analysis above, the formulated hypotheses are answered below.

H1: Knowledge claims found within EP tweets are associated with a higher count of retweets.

As the data in table 4.2 shows, knowledge claims have a higher effect on the retweet count. Therefore, the null hypothesis can be disproved. The results above point toward a higher retweet count being associated with knowledge claims.

H2: There are differences found between original tweets and

retweets.

As shown above in table 4.3, differences between original tweets and retweets could be measured. This is to say that the effects are not equal, and the null hypothesis can be disproved. According to the reviewed literature, the analysis section above pinpointed this observation on the different usage of knowledge claims in narrative initiating and narrative challenging tweets.

H3: The effect of knowledge claims on retweet count varies with party family affiliation of the EP

Hypothesis three can not be supported as the data available seems to be too thin and not fit for the model at hand. It appears impossible to make out any systemic effect of knowledge claims on narrative diffusion across party families. Thus, the null hypothesis can not be rejected. This does not mean that there is no systemic effect associated with party families. It simply means that the model discussed above does not provide enough concrete evidence and is not suited for discussing hypothesis three.

Chapter 5

Conclusion

The regression analysis shows that knowledge claims positively affect the retweet count of tweets authored by EPs. Thus, answering the research question as follows:

> *"Tweets containing knowledge claims show a higher retweet count, everything else being equal. Thus, knowledge claims affect the diffusion of European Paliarmentarian Tweets between 2017 and 2019 positively."*

According to Boswell et al. (2011), including references to knowledge and evidence in narratives boosts the perceived validity of the narrative. Furthermore, Jones & McBeth (2010) include the perceived expertise of an actor on the issue at hand as an essential part of narrator trust, which increases the persuasiveness of a narrative. Thus, this thesis argues that political actors can increase their perceived expertise on particular policy problems by including knowledge claims in their narratives, increasing the persuasiveness of their narratives. In the context of political communication on Twitter, this effect leads to increased diffusion of the tweet as more and more users get transported by the narrative.

Furthermore, when distinguishing between original tweets and retweets, an additional effect can be observed. Knowledge claims within narrative initiating tweets, i.e. original tweets, positively affect retweet count, while they negatively affect the retweet count of narrative challenging tweets, i.e. retweets. Whether a retweet challenges another narrative is hard to tell from the chosen method. However, assuming that all messaging of political actors on Twitter serves to communicate politically, it can be said that direct reactions of political actors on other users have a particular strategic aim. This aim can either be to support the retweeted message or to attack it. In this sense, retweets of political actors are always competitive. The competitive use of knowledge claims eventually leads to competing truths. One actor will claim (A) to be true due to study (X), while another actor will claim (A) to be false due to study (Y). According to Boswell et al. (2011), this competitive use of knowledge and evidence leads to distrust among constituencies. Thus, it negatively affects narrator trust and persuasiveness, which is one possible explanation of why knowledge claims in retweets negatively affect retweet count.

The generalization of these findings to a setting outside of social media is challenging. The working definition of what constitutes a narrative on Twitter is minimal and doesn't hold in situations allowing for more elaborate discourse. Furthermore, social behaviour on social media is different from how people behave in a real-world setting. Social media is much more fast-paced and short-lived, and individuals are engaging with one another largely anonymously (Margetts et al., 2016). The degree of diffusion is directly visible through the retweet count displayed beneath each tweet, which is usually unknown to the individual outside of Twitter (Margetts et al., 2016). However, the user cannot see why the majority of people have retweeted something. Additionally, engaging in political discussion and contributing to narrative diffusion on Twitter is much less costly than in the real world. This is not to say that this study has no real-world implications. Social media has long become a big part of political communication, and political messages on Twitter frequently make headlines and are discussed on different, more traditional platforms.

As discussed above, the distribution of the observed data points toward the presence of thresholds and tipping points in social media messaging on Twitter, which affects how tweets diffuse and impact any measurements that researchers might want to do on this data. As Margetts et al. (2016) point out, social media messaging might allow researchers to test the presence of tipping points in collective behaviour proposed by Schelling (2006) as the degree of diffusion is visible to participating individuals, which is usually not the case in real-world scenarios. Thus, this thesis applied a log-transformation to account for the effect of tipping points and increase the robustness of the applied regressions.

However, there are several remaining limitations of the applied method. Firstly, the chosen method to measure differences in the use of knowledge claims across party families could not produce any insights. Thus, the respective hypothesis could be answered convincingly. Nonetheless, the party family perspective seems a relevant one and should be addressed in future research. As the explorative analysis of hashtags in fig. 3.5 shows, there appear to be topical differences in the use of knowledge claims. For example, topics associated with Brexit and the separatism of Catalonia seem to be associated with non-knowledge claim tweets, while topics related to climate and sustainability seem to appear more frequently among knowledge claim tweets. Whether this is due to the nature of the topic itself or due to the party families by which these topics are addressed remains unanswered.

Secondly, it is a challenge to fully understand to what extend variables such as follower count, verified status, or friend count have on retweet count and how this affects the measured effect of knowledge claims. The impact of each covariate is expected to change over time as Twitter keeps developing its software (van Vliet et al., 2020). One crucial concern is that the Twitter algorithm may have changed over the period of data collection, which would pose a threat to the comparability of data collected early and data collected later. Furthermore, when attempting to replicate this study with more recent data, comparability may be at stake. Unfortunately, there is no way of controlling for the effect of the Twitter algorithm, as Twitter does not provide any information about the details of their software (van Vliet et al., 2020). This thesis can do little more than pointing out this possible bias.

Thirdly, while social data has never before been available at comparable volume, velocity, or variety (Lukoianova & Rubin, 2014), the delineation of the population and extreme variance within the data pose further challenges to researchers. This study agrees with the scholarly discourse on using big data for social science research (see Lukoianova & Rubin, 2014; van Vliet et al., 2020) and points toward the uncertainty associated with it. Veracity is frequently quoted as an additional 'V' in the context of big data — next to volume, velocity, or variety (Lukoianova & Rubin, 2014). In the context of social media data, veracity refers to the realization that big data is associated with biases, ambiguities, and inaccuracies (Lukoianova & Rubin, 2014). Scholars like van Vliet et al. (2020) attempt to address these issues by providing a database of social media data that enables researchers to identify and account for veracity and reduce inference errors to improve accuracy and generate insights.

This thesis engages veracity by defining a clear sample population of English language tweets written by EPs from Member States between September 2017 and April 2019. As pointed out by van Vliet et al. (2020), focusing Twitter research on a population of users rather than hashtags makes the data comparable as future research can anchor on the same population. Using hashtags to identify a sample population poses the threat that individuals in the sample will change when the research is reproduced. Furthermore, as recommended by Raban & Rabin (2009), the data has been log-transformed to normalize it and prepare it for linear regression analysis.

Thus, this thesis has taken the necessary steps to reduce inference errors and has confidence in the findings. Furthermore, the empirical findings were validated against the theoretical framework and could assess the formulated hypotheses. By answering the research question, this thesis met the formulated goals and could provide a perspective to the study of the diffusion of narratives in social media messaging.

The argument of the paradox of the co-production of science and policy (Jasanoff, 2004) provides intriguing grounds for further investigation. The competitive use of knowledge claims appears to have an effect on narrative diffusion distinct to the narrative validating application of knowledge claims. It is recommended for future research to utilize a coding method to identify narratives according to the NPF codebook provided in Shanahan et al. (2018). Providing a way to identify tweets oriented toward a concrete policy problem should provide an insightful dimension to determine the effect of knowledge claims on narrative persuasiveness.

Another perspective for future research is to focus on the original and retweet distinction discovered in the data. As pointed out above, there are statistically significant differences between tweets reacting to other users and tweets that start a new discussion. The proposed explanation for this difference must be further examined in future research as it may provide insights into how political actors can strategically place knowledge claims in their engagement with the public on Twitter.

Practically, the findings presented in this thesis are valuable to political actors who use Twitter as a platform to communicate with their constituency. As expected by the theoretical discussion, the results show a positive effect on retweet count overall. However, they also find situations in which they might harm the diffusion of narratives. Thus, political actors should strategically place knowledge claims when initiating a discussion to increase narrative persuasiveness but should refrain from using them when reacting to other users. Besides the practical application of this research for political actors, this thesis hopes to inform the public about viewing and interpreting knowledge claims in public discourse.

Chapter 6

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Chapter 7

Declaration of Originality

I, Philipp Kohn, Am Stemmersberg 15, 46119 Oberhausen, Germany, s2693240, by signing this, declare on oath that I prepared this thesis on my own and without any external help. Furthermore I declare that I marked every passage that I literally or logically extracted from released or unreleased sources. I did also not use sources or other means apart from the cited ones.

I declare on oath that I did the aforementioned specifications in all conscience, that the provided information is true, and that I did not conceal anything.

I am aware that:

Noncompliance will be reported, the paper will be graded as failed, I may be ex-matriculated or excluded from further examinations at theFaculty of Governance and Global affairs in case of plagiarism. I am also aware of the fact that an inaccurate statutory declaration is punishable.

Oberhausen, Germany, June 10, 2021