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Online Networks and Offline Policy

A Study on Influence in the Finnish Climate Change Policy Network

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Master’s Thesis

Author:

Anniina Penttilä

Supervisors:

Ted Hsuan Yun Chen

Mikko Mattila

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Abstract

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This master's thesis investigates whether and how influence in policy networks can be studied with Twitter data. Actor influence is of vast interest to policy scholars, as it has been seen to have a notable impact on forming public policies. However, measuring influence is complex, which can limit the scope of research on influence in policy. Exploring social media sources has great potential for providing alternative data for studies concerned with actor influence in policy processes.

This study makes two contributions to the field of policy studies. Firstly, it examines whether the influence in real-life policy networks corresponds to the influence in Twitter networks. In the analysis, offline influence is measured as formal decision-making power and informal, reputation-based influence. Online influence is measured by actor centrality on Twitter. Secondly, it looks more closely at how influencing works in online networks. The analysis examines how network interactions affect online influence and whether connections from actors influential in the offline policy network add to an actor's influence on social media.

The empirical object of this thesis is the case of the Finnish climate policy network. The analysis is conducted by combining two data sets: offline influence perceptions reported by the network members in a survey and Twitter data consisting of retweets between the same network actors. An actor retweeting another on Twitter is the dependent variable in the analysis. Tie formation in the network is explored with exponential random graph modeling (ERGM) that allows modeling the tie formation patterns on Twitter conditional on actor influence while accounting for other factors posited to contribute to tie formation.

The main results are as follows. (1) Actors that are perceived as the most influential in the offline policy network are also the most influential on Twitter; (2) Having formal powers, such as being a government agency, is not associated with more incoming ties online; (3) Being influential online begets even more ties due to the status granted by the central position and (4) having online ties from actors that are influential offline does not add to an actor's influence.

This thesis shows that influence amongst policy network actors can be studied using social media data. The results also have practical implications by demonstrating that actor influence is constructed in interaction over time. The fact that ties from influential actors did not lead to more incoming ties implies that social media centrality cannot be fully equated with real-life influence. These results encourage policy network researchers to continue exploring the use of observable digital networks in research on actor influence.

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Tämä maisterintutkielma tarkastelee vaikutusvaltaisuuden muodostumista politiikkaverkostoissa Twitter-datan avulla. Toimijoiden vaikutusvaltaisuus on laajan kiinnostuksen kohde politiikkaverkostojen tutkimuksessa, koska sillä on nähty olevan suurta merkitystä poliittisten linjausten muodostamisessa. Verkostojen vaikutusvallan mittaamisen ollessa hankalaa, sosiaalisesta mediasta kerätty data tarjoaa suurta potentiaalia toimijoiden vaikutusvallasta tehtävän tutkimuksen laajentamiseen.

Tämä tutkielma tekee kaksi kontribuutiota politiikan tutkimuksen alalla. Ensinnäkin sen tavoitteena on tarkastella, heijastuuko vaikutusvaltaisuus tosielämän politiikkaverkostoissa vaikutusvaltaan Twitter-verkostoissa. Analyysissä tosielämän vaikutusvaltaa mitataan sekä formaalina päätöksentekovaltana, että epävirallisena, maineeseen perustuvana vaikutusvaltana. Twitter-verkostoissa vaikutusvaltaa mitataan toimijan keskeisenä sijaintina verkostossa. Toiseksi tutkielmassa syvennytään siihen, miten vaikutusvaltaa käytetään sosiaalisessa mediassa. Analyysissä tarkastellaan, saavatko suositut käyttäjät enemmän verkostoyhteyksiä ja kasvattavatko yhteydet vaikutusvaltaisiin verkostojäseniin toimijoiden vaikutusvaltaa Twitterissä.

Suomen ilmastopolitiikan verkosto toimii tutkielman empiirisenä tutkimuskohteena. Analyysi yhdistää kaksi aineistoa, kyselytutkimuksen, jossa on kartoitettu verkoston osallistujien itsensä käsityksiä eri toimijoiden vaikutusvaltaisuudesta, ja Twitter-aineiston, joka sisältää toimijoiden välisiä uudelleentwiittauksia (retweet) Twitterissä. Analyysin selitettävä muuttuja on retweet-verkoston yhteys kahden toimijan välillä. Verkostoyhteyksiä tutkitaan *exponential random graph modeling* (ERGM) tilastomenetelmän avulla. ERGM-menetelmä mallintaa yhteyksien ilmentymistä ottaen samanaikaisesti huomioon sekä vaikutusvaltaisuuden toimijatasolla, että muita yhteyksien muodostumiseen vaikuttavia tekijöitä verkostotasolla.

Tutkielman pääasialliset tulokset ovat: (1) Toimijat, joita pidetään vaikutusvaltaisina politiikkaverkostossa ovat vaikutusvaltaisia myös Twitter-verkostossa; (2) Formaali päätöksentekovalta, jota esimerkiksi puolueet, valtion virastot ja ministeriöt edustavat, ei ole kytköksissä Twitter-vaikutusvaltaan; (3) Suositut käyttäjät saavat enemmän Twitter-yhteyksiä keskeisen aseman tuoman statuksen myötä; (4) yhteydet politiikkaverkoston vaikutusvaltaisilta toimijoilta eivät lisää käyttäjän vaikutusvaltaa sosiaalisessa mediassa. Tämä tutkielma osoittaa, että verkostotoimijoiden välistä vaikutusvaltaa voi tarkastella sosiaalisesta mediasta kerättyä dataa käyttäen. Tulokset havainnollistavat myös, että vaikutusvalta muodostuu toimijoiden välisessä kanssakäymisessä. Sosiaalisen median yhteyksiä ei voida kuitenkaan pitää täysin yhteensopivana mittarina tosielämän vaikutusvallalle, sillä yhteydet vaikutusvaltaisiin toimijoihin eivät johtaneet keskeisempään asemaan Twitter-verkostossa.

1. Introduction

Influence and power are the most central concepts in the study of public policies, yet it is widely disputed how they should be defined and measured. In policy sciences, influence is, to an increasing extent, studied by investigating relationships between actors that operate within the policy arena in focus. This line of research is referred to as policy network studies. Examining which actors exert the most influence in policy networks has intrigued researchers concerned with studying policymaking processes for decades (Cox & Jacobson, 1973; Ingold & Leifeld, 2016; Laumann & Knoke, 1987; Pfeffer, 1981). The most used method for determining influence is surveying the policy network actors on which of their peers they perceive to be the most influential. Although surveys provide a fitting proxy for influence dynamics, the lack of diversity in study methods has been seen to constrain the possibilities and the development of policy network studies (Henry et al., 2012).

In policy studies, a growing body of research has started to study policy network interactions with the help of online networks (Yi & Scholz, 2016; Yoon & Park, 2014). Especially the microblogging service Twitter has attracted the attention of policy network scholars. During the past decade, Twitter has grown to be the most used online platform for policy debates between policymakers, interest groups, and the public (Weller et al., 2014). The site poses great potential for network scholars due to its relevance as an enabler and a facilitator of low-threshold policy discussions and the easily accessible data it offers for research. As common to social media sites, interpersonal relationships on Twitter are organized through social networks. This has answered the call of researchers in great need of observable networks for studies on relationships between individuals and organizations.

Earlier research has found there exists a connection between online interaction and offline behavior, for example, in elections (Bentivegna et al., 2022; Bond et al., 2012; Freelon & Karpf, 2015; Jones et al., 2017; Maruyama et al., 2014), demonstrations (Larson et al., 2019; Steinert-Threlkeld et al., 2015), and crises (Acar & Muraki, 2011; Imran et al., 2016). This line of literature shows that online platforms have a vital role in shaping interaction in real-life events and gives reason to believe that even policy actors' behavior can be studied with the help of social media data.

To date, the potential of Twitter in research on influence is still relatively unexplored. Earlier research on influence within computer sciences scholarship has concluded that occupying a central position on Twitter is connected to an actor being influential within the platform (Bakshy et al., 2011; Cha et al., 2010; Huberman et al., 2008; Kwak et al., 2010; Romero et al., 2011). The literature does not address to which extent influence amongst policy network actors online could be seen to translate to influence in offline policy processes. An exception to this makes Cossu et al. (2015) that find that offline influencers do not exert influence on Twitter. However, the authors measure influence based on the actors' own activity, not their impact on their surroundings. The approach of my study emphasizes interaction as a basis for influence, which can be argued to correspond better to the idea of how actors exert influence in policy networks. Thus, further research is needed to conclude whether online influence can be used to study influence in offline policy networks.

The earlier quantitative research on influence does not reflect the importance of social interaction as a basis for online influence. Network literature has established a broad range of interaction patterns contributing to tie formation within policy networks. It is yet to be tested, whether these effects exist in online interaction between offline policy actors. Amongst the most common patterns is the preferential attachment or 'popularity effect', where highly central actors attract even more ties to themselves due to their status of being popular or well-resourced (Barabási & Albert, 1999). Earlier research does not generally discriminate between types of ties contributing to this popularity. However, it could seem possible that, as it has been concluded in policy network sciences, powerful contacts can add to an actor's influence on Twitter (Ingold & Leifeld, 2016).

This thesis aims to address these literature gaps and analyze different aspects of influence in Twitter networks. Firstly, I use influence, as reported by policy network members, as a determinant of the probability of receiving retweets on Twitter. Seeing that influence in real life gets translated to centrality in Twitter networks would support the notion that social media ties can be used as directly observable policy network relations and break new grounds for studying influence in policy studies. Secondly, I examine whether the popularity effect leads to central actors attracting even more ties on Twitter and whether retweets from particularly influential policy actors bolster this effect. Exploring the impacts of these social tendencies on actor centrality on Twitter would show that interaction shapes influence perceptions and allow the analysis to discuss the practical applications of influential real-life actors being central in online networks.

The objectives of this study can be summarized in the following research questions:

1. Are influential policy actors central on Twitter?
2. On Twitter, do highly central actors attract even more ties?
3. On Twitter, do ties from influential policy actors add to an actor’s centrality?

To briefly sum up the main results, the analysis finds that the actors cited as influential by their peers are the most central ones on Twitter. The result shows that Twitter centrality can be used as a proxy for offline policy actor influence. It also supports continued examinations of social media's potential in policy studies. It can also be inferred that Twitter centrality begets more ties, which means that online influence affects which actors occupy central positions and get their voices heard on Twitter networks. The analysis could, however, not confirm that an actor’s real-life influence could affect another actor’s centrality on Twitter, as connections from powerful contacts did not lead to an actor receiving more ties. This finding points out that behavior on Twitter should be interpreted with caution in studies of offline relationships.

The empirical analysis looks at the case of the Finnish climate policy network during the years 2018-2021. A policy network concerned with climate change poses an apt object for the study of influence. Climate change policymaking is characterized by a wide range of competing interests, the incorporation of a broad range of actors, and unclarity on the scope of the problems and their solutions (Lemos & Agrawal, 2006; Rittel & Webber, 1973). As no single authority has the power, information, or resources to make comprehensively effective decisions, politicians and government representatives need to build contacts with other actors with interest and expertise in the issues. In this exchange, groups such as business sector representatives, researchers, and civil society organizations get to push for their preferred policy alternatives to turn them into actual policy (Head, 2008).

Furthermore, more research on actor influence is needed to examine the reasons behind a country's status as a 'leader' or 'laggard' in climate mitigation policies. Earlier research on climate policymaking has found that factors such as government constellation (Harrison et al., 2010; Tobin, 2017), committing to transnational mitigation targets (Fankhauser et al., 2016; Jänicke, 2005; Liefferink et al., 2009), institutional design (Jänicke & Weidner, 1995; Knill et al., 2010; Madden, 2014), political culture (Jänicke, 1995), citizen engagement (Harrison et al., 2010), degree of economic development (Börzel, 2002; Lenschow et al., 2005), and presence of powerful opinion leaders (Nisbet & Kotcher, 2009) can affect the event or absence of ambitious climate policy decisions. As no single explanation has been found to lead to climate policy ambition or the lack of it, more research is needed to examine how different actors can influence climate policymaking.

Finnish climate policies pose a fruitful object for analysis as the country's climate policymaking has for decades been characterized by a weak track record in emissions reduction in comparison to its peers (Koch & Fritz, 2014). In 2019 there could be seen a change in paradigm as Finland declared to become carbon neutral by 2035. However, by the latest estimates, this goal is eluding the government. In earlier research, the country's status as a climate policy laggard has been concluded to be a result of business and industry organizations being highly influential and tightly connected to central political decision-makers (Gronow & Ylä-Anttila, 2019). The unclarity in the course of the last few years of Finnish climate policies calls for more research on influence dynamics within the policy network.

My thesis contributes to several lines of research within policy network studies. Firstly, I add to the growing body of research where policy networks are studied with the help of social media data. I make one of the first contributions within policy sciences where influence in real real-life is used as a determinator for the probability of ties forming on Twitter. Secondly, I illustrate how tools of statistical network analysis can be used to examine influence construction in online networks. By treating influence as a reputation built in social interaction, I can examine how social tendencies affect the processes of online tie formation between actors that also interact in a local offline network. Thirdly, by focusing on the case study of the climate policy network in Finland, I shed light on the climate policy arena on Twitter during the formative period of 2018-2021.

The rest of the thesis is organized as follows. In Chapter 2, I go through the theoretical framework of how influence in policy networks is constructed and elaborate on the shortages of traditional ways of measuring actor influence. Based on earlier research, I set the central hypothesis of my study, that studying the processes with which influence is built on social media can provide new insights to influence in policy networks. Chapter 3 presents the case of the Finnish climate policy network. I elaborate on earlier research on influence within the network and illustrate how central actors' reluctance towards ambitious policies has shaped the policymaking arena in Finland. Chapter 4 consists of data and methods sections. In the data description part, I go deeper into the process of the data collection procedures for the two data sets used in the analysis. I also present the most influential actors as measured in both data sets and describe the activity on Twitter during the study period of 2018-2021. The chapter ends with clarification on the method of exponential random graph modeling and the model specification. Chapter 5 goes through the results of the data analysis. In Chapter 6, I present the findings in the context of policy network literature on actor influence and discuss the study design's strengths and weaknesses. In Chapter 7, I present my concluding remarks and suggestions for further research.

2. Theoretical framework

2.1. Policy networks

The study of policy networks has been one of the major focus areas in public policy literature over the past decades. Policy network studies are said to originate from the works of two schools, inter-organizational studies, and social network analysis. The inter-organizational perspective posits that organizations cooperate as they depend on resources that others possess in the same policy system they operate within. This interdependency between organizations sparked an interest in studying how public policy actors participate in collective decision-making in networks (Adam & Kriesi, 2007; Rhodes, 2006). In social network analysis, on the other hand, the focus shifted from relationships between individuals to collective entities in political subsystems. Instead of solely looking at individual behavior, early policy network scholars started applying the practices of social networks to organizations in political elite subsystems (Laumann & Knoke, 1987).

According to network terminology, networks consist of two essential elements: network members (even called nodes, actors, or participants) and connections in between them (even called ties, edges, or structures). In a seminal work on policy networks, Laumann and Knoke (1987, p. 10) describe the policy network as a 'set of actors with major concerns about a substantive area, whose preferences and actions on policy events must be taken into account by the other domain participants'. Another description of policy networks by Rhodes (2006, p. 426) states that policy networks are 'sets of formal institutional and informal linkages between governmental and other actors structured around shared if endlessly negotiated beliefs and interest in public policy making and implementation'. Furthermore, Rhodes (2006, p. 426) states that the 'actors are interdependent and policy emerges from the interactions between them'. As articulated in these descriptions, the focus on interdependence and interaction between network participants is manifested in the influence perception within the policy network studied in this thesis.

The literature on policy network analysis is broad, and the term is used interchangeably for different purposes and contexts. Three main fields on the applications of the concept of policy network can be distinguished: (1) as a metaphor or an analytical framework for describing the interaction between public and private actors in public policymaking, (2) as the formalized way of conducting quantitative analysis with the help of statistical tools (3) as a theory for reforming and forming the public administration (Adam & Kriesi, 2007; Raab & Kenis, 2007; Rhodes, 2006). Some scholars highlight even the policy network concept's value as a theory (Rhodes, 2006). In contrast, others have argued that the ambiguity on what even could be counted as 'network theory' makes labeling the approach as a theoretical framework questionable (Dowding, 1995; Kenis & Schneider, 1991; Raab & Kenis, 2007).

During the early years of developing policy network analysis, the approach was criticized for the 'Babylonian chaos' of diverging applications and the allegedly purely theoretical nature of the concept policy network (Börzel, 1998; Dowding, 1995). However, the advances made during the past few decades have proven network analysis to provide a valuable framework for analyzing relationships between actors in the public sphere. The developments made in statistical network analysis allow researchers to study social network theories quantitatively, which has yielded a broad line of research showing that the theorized network processes indeed form the underlying structures within a network (M. Fischer & Sciarini, 2015; Freeman, 1978; Goodreau et al., 2009; Heaney, 2014; Ingold & Leifeld, 2016, 2016; Lubell et al., 2012).

In this thesis, I use the 'lens of networks' in two ways, both as an analytical framework and a statistical tool. I first present the climate policymaking arena as a network to describe the actors active in the field of climate policymaking in Finland and that need to be considered when examining influence within the network. The organizing concept of a network brings structure to the relationships between all the relevant actors and gathers them metaphorically around the policy issue of interest, climate policies. Secondly, I use the statistical tools of network analysis to examine the network's properties quantitatively and draw inferences on the network's structure. With this approach, I can study large quantities of data with interactions between the network members to determine which factors contribute to ties forming in the policymaking network, as posited in the research questions.

2.2. Influence in policy networks

A central concept for my study is the influence of policy network actors. The exact definitions of influence and power are broadly disputed in political sciences (Dahl, 1957; Lukes, 2005), which is why an elaborate discussion on the characteristics and differences between the two is beyond the scope of this thesis. As common to policy studies, I treat the concept of influence as a reputational measure that emphasizes the role of interaction as a basis for actor influence (Cox & Jacobson, 1973). Betsill and Corell (2007, p. 24) have defined influence to occur 'when one actor intentionally communicates to another so as to alter the latter's behavior from what would have occurred otherwise'. According to Vecchio (2007), exerting influence is interacting with others and using particular tactics to advocate for the desired outcome. I utilize these descriptions as they both underline the relational nature of influence as a source of power.

The literature distinguishes between two sources of influence: formal powers deriving from an actor's institutionalized status and reputational influence based on social structures (Ingold & Leifeld, 2016). Formal power entails the authority to make binding decisions regarding public policies. It is mainly assigned to public authorities, elected officials, and political parties. Informal reputational influence, on the other hand, derives from the relationships within a policy network. It is not determined by the institutional status of an actor but rather by the reputation of being able to exert influence in policy on the arena in which the actor operates (Heaney, 2014). Even though formal authority is an inarguably strong indicator of reputational power, it is not the sole determinant as social authority can have a significant impact in which views are accounted for (Cox & Jacobson, 1973; Pfeffer, 1981). In the analysis, I examine the relationship between the two sources of policy impact by testing whether formal powers and informal reputational influence are indicative of an actor's influence on Twitter.

Earlier studies on policy networks have shown that an actor with a reputation of being influential is perceived as capable of having a notable effect on decision-making, and that reputation, indeed, is a fitting proxy for power. Fischer and Sciarini (2015) show that reputational influence ‘measures what it ought to measure’, as several indications of influence in policy in their study correlate with influence perceived influence. Carpenter (2010) and Carpenter and Krause (2012) argue that reputational power is crucial for all organizations, even for governmental actors, as reputation forms organizational behavior and can bolster or diminish an organization’s possibilities to have a notable impact on policy. Moreover, as stated by the resource dependency theory, organizations are often highly dependent on critical resources they can only obtain from their surrounding environment (Pfeffer & Salancik, 1978). As influence is the most crucial resource in policymaking, all actors, including those with formal powers, seek to gain the reputation of being influential in impacting the policy issue at hand. The argument of social dynamics affecting policymaking is strengthened by the increasing amount of empirical research showing that network structures can explain different policy outcomes taking place (Daugbjerg, 1998; Sandström & Carlsson, 2008; Villadsen, 2011).

Reputational influence matters not only because an influential actor can affect the policy issue at hand but also because the influential actor can affect the influence of others. As argued by Ingold and Leifeld (2016), an actor connected to organizations with vital resources is perceived as more influential within the network. Thus, powerful actors can have an impact on less influential actors’ perceived influence by merely establishing contact with them. Connections to influential actors are essential for any actor without formal decision-making powers, as building communication channels with influential decision-makers is also de facto the only way to gain influence in policy (Rietig, 2016). Perceived influence is especially fitting to study in social media networks, as connections in between actors are open for all rest of the network to see. An influential actor A building a connection to the less powerful actor B can be seen to hold a signaling effect on the network. As a communication channel exists between the two actors, B can use the contact to turn their views into policy. The notion that B’s influence derives from that of A emphasizes also the meaning of relationships as a source of power.

Since influence is highly based on social dynamics rather than an actor’s institutional status, it can be significantly affected by notable changes in the policymaking environment. Formative events such as new issues emerging and capturing the attention of public policymakers or a change in government constellation after elections can alter the power dynamics between policy participants and introduce new actors and interests to the policy arena. Kingdon (2014) has famously coined these events as windows of opportunity. According to Kingdon's definition, a policy window is 'an opportunity for advocates of proposals to push their per solutions, or to push attention to their special problems' (Kingdon, 2014, p. 165). Following Kingdon's typology, policy windows open when a policy problem fills three criteria: there is a clearly formulated and compelling policy problem, solutions available to solve it, and political incentives to address the issue. An actor that succeeds in describing an apparent policy problem, presenting solutions to it, or gaining political support for addressing the issue, can then ramp up their influence at times when the topic is hot and raised high up on the political agenda (Kingdon, 2014).

The dynamic nature of influence makes it not only complex to define but also to study empirically. Identification of actors with formal powers is relatively simple as it can be done merely by looking at actors' organizational affiliations. However, the task gets trickier when determining which organizations have been the most influential ones in a specific policy process. It is not unthinkable to imagine a situation where a political party with formal powers would have participated in a policy process but not have even tried to significantly impact the issue as it was not of great concern to them. I.e., obtaining formal powers does not necessarily mean that they always would be willing to or successful in exerting influence in a policy question (Dahl, 1957). Moreover, even knowing that the party was highly involved in the policy process, simply observing the policy outcome might not shed much light on to which extent it managed to influence the policy and other actors during the decision-making process.

The influence of actors without formal powers is often even more complex to determine. Observing expert or interest group participation in institutionalized decision-making forums or reading statements they file for policy proposals could give a clue on which actors are interested in the issue. Still, none of those indicators say anything about whether an actor's views are accounted for. Moreover, many interest groups seek to impact policies in informal ways by lobbying, attracting media coverage or engaging in civic participation outside the actual policymaking processes (Betsill & Corell, 2008; Gulbrandsen & Andresen, 2004; Rietig, 2016). Thus, in determining which actors have been the most influential ones in a policy, mere records on which organizations have participated in the formal process would give superficial information on which interests are echoed in the final approach.

2.3. Offline data: surveying network members

To overcome the difficulties in tracing down the exact actors behind specific policies, influence is commonly measured as the reputational influence of network participants. The most used method for determining reputational influence is surveying, or in cases of more in-depth analysis on smaller networks, interviewing the members of the networks on whom they perceive to be most influential ones (Henry et al., 2012; Marsden, 1990; Pfeffer, 1981). In surveys, respondents are typically given a list of all the policy actors and asked to indicate which ones they perceive as the most influential ones. Especially in cases where the network boundaries are unclear to the researchers, respondents may be asked to freely nominate all organizations they see as particularly influential without choosing from a pre-processed list. The method has been broadly accepted as a fitting way of measuring influence as reputation has been shown to provide a reasonable proxy for the actual power relations in networks (Carpenter & Krause, 2012; M. Fischer & Sciarini, 2015).

For decades, surveying has provided network scientists nearly the only feasible estimate for influence dynamics within collective entities of individuals or organizations. Even in the analysis of this thesis, I use a data set that consists of results from a survey measuring network actors' influence, as it is the most accurate method available for determining actor influence in policy studies. Simply asking the network members is also the most intuitive way to find out the most powerful ones in the network, as they are the ones with the closest information on the policy process. However, as with most research methods in social sciences, even surveying has its pitfalls, and several network scientists have discussed the problems and biases associated with survey-based network research.

In policy network studies, it is often the organizational relationships that are of interest. The surveys are, however, filled by one or a few representatives of the organizations. For the researcher, there are few ways to be sure that the responding representative has sufficient capacity to correctly evaluate the influence of others on behalf of the organization (Berardo et al., 2020). One respondent can only provide their view on influence dynamics, which mirrors solely one perspective on the relationships between all the individuals within the policy network organizations (Lubell et al., 2012). Researchers seek to minimize this risk by targeting representatives who have participated in policymaking and possess a complete view of the policy processes. The risk cannot be eliminated entirely in cases where such representatives are unavailable or where several sectors within an organization have been involved. Moreover, targeting specific individuals or sectors is not always feasible, especially in online surveys to more extensive networks. In such cases, researchers must rely on the organization's perceptions of who is suitable to respond to the study.

Even though a respondent would have complete information on which organizations have been the most significant in the policy process, network studies have identified several biases that might affect perceptions of the influence of others. A tendency theorized especially in networks with rivaling advocacy coalitions is the 'devil shift', which makes respondents biased to perceive the opposing side as more powerful than they truly are (Sabatier, 1998). Another line of research has concluded the opposite, that actors would see their collaboration partners as more influential (Fischer & Sciarini, 2015; Ingold & Leifeld, 2016). Some evidence points also to the fact that organization similarity, a well-documented contributor to tie formation in networks (e.g. Goodreau et al., 2009), can lead to homophily bias and make respondents assess an organization that is similar in essential aspects as more influential (Heaney, 2014); see however also (M. Fischer & Sciarini, 2015).

The complexity of defining network boundaries accurately can lead to biases deriving from the survey design (Henry et al., 2012). Researchers typically aim to facilitate the task of naming relations by providing a pre-processed roster of all the participants in policy to respondents to choose from. If the list is not carefully compiled, it could affect the results and make actors outside of the roster look less powerful. Even though respondents commonly are allowed to name actors outside the provided list, the roster-based design can make organizations biased to only consider the listed actors (Ibid.). Including all thinkable policy organizations in the roster, assuming that such a list would be possible to compile, entails the risk of respondent fatigue as respondents might give up reading the complete list.

An opposite approach of letting the respondents freely name the organizations that they perceive as influential can be highly affected by the limits of respondents' recall capacities (Henry et al., 2012). Relying on individuals' memory as a data source poses notable constraints to studying large networks and network processes and events from far in the past. Limits of respondents' recall capacities can lead to recall bias which means that it is likely, that an individual is not able to remember all organizations that they hold the most influential ones as they are not necessarily all easily accessible in working memory during the surveying situation (Bernard et al., 1979, 1982).

Furthermore, conducting surveys is resource-demanding as it is both time-consuming and economically costly, which can limit the scope of studies conducted on influence in networks (Hayes & Scott, 2018). Surveys on networks are also especially prone to low response rates, as the absence of only one central actor poses a severe liability to the internal validity of the results (Berardo et al., 2020). The crucial need for the great majority of network members to contribute to surveys poses a constraint to conducting temporal analysis on policy networks, as surveying the same group of actors repeatedly often leads to declining response rates (Laurie et al., 1999). The biasedness of results resulting from high non-respondent rates can be diminished based on the knowledge of which types of actors have omitted to respond. However, the results are still the most accurate when all or most network actors contribute to the survey (Yi & Scholz, 2016). Thus, even though surveying is the by-far most appropriate tool for influence determination, it can be unsuitable for certain types of policy network research.

2.4. Online data: networks in social media

The overall modest ability to observe networks empirically has long constrained the use of statistical tools in network sciences (Henry et al., 2012). To overcome the hazards associated with survey-based network research and to widen the scope of empirical research on policy actor influence, exploring complementary data sources is thus well motivated. During the past decade, the emergence of social media as a policy discussion arena has offered policy network researchers a myriad of easily accessible data for analysis. Compared to survey-based research, studying digital networks has some clear advantages. Social media sites are commonly organized as (semi-)open networks where direct communication between individuals and organizations occurs in real time. As opposed to observing, for example, formal participation within political institutions or public dialogue in traditional media, there are no gatekeepers restricting participation or shaping the context of interaction. On social media, communication between different parties occurs openly without any intermediates, and it is observable to and traceable in time and place (Barberá & Steinert-Threlkeld, 2020).

With social media data, social scientists also get the rare opportunity to directly observe actual network behavior without the interference of the study objects (Barberá & Steinert-Threlkeld, 2020). As such, research is not affected by conscious or unconscious biases or the limitations of individuals' recall capacities. Digital networks allow collecting and analyzing large sets of fine-grained temporal data at low or no cost (Hayes & Scott, 2018). Exploring a policy network during a more extended period of time allows for comparing interactions during different policy discussions, as well as studying the effects of formative policy events on interactions within the network. Moreover, in policy network studies, the problem of non-respondent rates can be dealt with by studying social media sites that contain the whole studied network.

Compared to other big social media platforms such as Facebook, Instagram, and Reddit, Twitter is a superior data source for policy network analysis. Twitter is a microblogging service where users post short messages, and tweets, to other users within the platform. The site is an especially apt study object as it is the number one social media used for political discussions between public, private, and third-sector actors (Barberá, 2015). Twitter allows unsymmetrical relations and thus does not require users to follow each other or accept each other as contacts to interact. The widely established norm on Twitter is setting accounts as public. As policy actors use Twitter broadly to communicate their views and participate in debates, few actors of interest in policy analysis set their accounts as private. This means that there are no obstacles in the way of interaction, and all the actors have had the same possibilities to establish contacts with others within the network. As all or the vast majority of the studied policy network actors have Twitter accounts that they use actively, the often-raised concern in network studies about Twitter users not representing the entire population is not applicable to policy networks (Barberá, 2015). Even in the data of this study, all 104 identified Finnish climate policy network members had an official Twitter account, which allowed collecting the complete information of relationships between the network members on Twitter.

Accessing Twitter data for research is relatively simple as Twitter's publicly available application programming interface (API) allows researchers to download data on Twitter users and connections in an easily processable form. This makes Twitter an exception to the standard rule of user data secrecy for research purposes of other social media giants (Edelson & McCoy, 2021). By providing this service, Twitter has become a significant data contributor to network research within different fields. Network research focusing mainly on one site is not entirely unproblematic (Olteanu et al., 2019). The difficulty of data collection on many other sites makes, however, Twitter often the only feasible choice of data for research.

It is not entirely straightforward that two very different kinds of connections, online and offline ties, could be used as equal in empirical network analysis (Berardo et al., 2020). However, earlier scholars have promisingly argued that observing links in social media networks can be considered an equally suitable alternative for measuring tie formation in real-life networks. In a study comparing online and offline social ties, Bisbee & Larson (2017) argue that real-world relationships can be analyzed by looking at connections via digital media and that no fundamental differences exist in the nature of the two types of ties. Jones et al. (2013) illustrate that public communication ties in social media sites, often referred to as 'weak ties', correlate with 'strong ties' such as private messages between actors, suggesting that observable exchange between actors in social networks could be used to analyze even stronger real-life connections in between the actors. Bond et al. (2012) show that voting behavior can be examined with the help of Facebook messages regarding voting.

Moreover, a growing body of research illustrates a relationship between policy actors' Twitter affiliations and 'real world' behavior in policymaking processes. Hayes and Scott (2018) show that collaboration patterns, as measured by surveys within a real-life network, correlate with Twitter ties forming between the same actors. Shmargad (2014) argues that retweeting can affect election outcomes. The effect of retweets differed by candidates' resources: more affluent candidates benefitted from direct retweets, whereas candidates with scarcer resources benefitted from receiving retweets from highly retweeted actors. Stier et al. (2018) find that political actors' communications on Twitter concentrate during periods of real-life policymaking, which supports the notion that political processes can be examined by observing activity in Twitter networks. In focusing on influence construction in policy networks, it is thus well motivated to study social networks.

A social media tie often used as a comparable connection to influence citations is retweeting on Twitter. Retweeting is an activity where an actor posts another user's tweet to their feed for their own Twitter network to see. A retweet can be accompanied by a comment from the ego or solely entail the original message of the alter (Boyd et al., 2010). Being retweeted has been widely accepted as one of the most fitting indicators for influence on social networks, as retweets are broadly understood as endorsements, agreement with the message, and signs of trust to the originator of the tweet (Araujo et al., 2017; Garimella et al., 2016; Metaxas et al., 2015). Retweeting has also been shown to primarily occur amongst homogenous actor groups such as political left- or right-wing actors (Boyd et al., 2010; Conover et al., 2011). Other communication methods, such as @-mentioning, are used in cases where the contact is established to express different views (Conover et al., 2011). The 'retweets do not equal endorsement' disclaimer found in several user profiles can also be used as anecdotal support for the broad view of retweets precisely as endorsements.

The increasing amount of research conducted with social media data has raised the question of whether the easily accessible data contains trade-offs that threaten the validity of results. Olteanu et al. (2019) argue that social media data contain biases that intrinsically affect research results. These biases derive from the built-in design of the websites and due to social community norms that affect how individuals behave on the platform (Olteanu et al., 2019). The effect of social media sites' design on the data collected from the platforms has also been discussed by Kulshrestha et al. (2017). The authors emphasize that it is essential for researchers to be aware of how design choices on social media sites form interactions. On Twitter, as well as on other sites, the functioning logic of algorithms is largely unknown. Even though they can affect the connections used in research on the site, they can be difficult or even impossible to attend to in data processing (Kulshrestha et al., 2017).

However, social media interactions are helpful in policy network research not only due to the feasibility and cost-effectiveness of the data collection but also due to the power social media exercises in forming public policies. Earlier policy research has widely recognized that visibility in traditional media can influence public opinion and even the views of decision-makers (Boykoff & Boykoff, 2007; Kingdon, 2014). It has also been shown that social media and traditional media have a reciprocal relationship and that they together create a hybrid media environment (Chadwick, 2013; Freelon & Karpf, 2015). With the increasing use of social media sites, studying influence formation on social media as opposed to traditional media is well justified.

2.4.1. Centrality

As presented above, I use the network approach to draw statistical inferences on the likelihood of hypothesized social tendencies forming the influence dynamics of the Twitter network. The network literature has identified several quantitative measures for determining influence in policy networks, such as degree centrality, betweenness centrality, and closeness centrality (Freeman, 1978). These measures look either at actors' direct contacts or broader network structures around the actor. As the three centralities have been seen to correlate (Faust, 1997), I use the measure amongst the most used ones, the in-degree centrality of an actor (Riquelme & González-Cantergiani, 2016). In-degree centrality counts the number of direct connections an actor receives within the network. The higher the in-degree centrality of an actor, the more central the actor's position is in the network.

Occupying a central position, i.e., having a high in-degree, is commonly used as a sign of influence, popularity, importance, and access to vital resources in a network (Borgatti et al., 2009; Brass, 1984; Faust, 1997; M. Fischer & Sciarini, 2015; Freeman, 1978; Sun & Tang, 2011). As concepts of centrality and influence intrinsically refer to the same phenomenon in network sciences, I will thus use the terms interchangeably in continuation. In earlier quantitative research on the influence on Twitter, a central position obtained through retweets from an active audience is often used as a sign of an actor exerting influence on its surrounding network (Badashian & Stroulia, 2016; Cha et al., 2010; Dubois & Gaffney, 2014; Kwak et al., 2010; Subbian & Melville, 2011; Vaccari & Valeriani, 2015). However, this line of studies has primarily been conducted within the field of computer sciences. It is also concerned mainly with studying word-of-mouth marketing and global Twitter virality in large global Twitter networks. Thus, further research with real-life networks as the study objective is needed to see whether being central on Twitter translates to influence in actual real-life networks.

Earlier attempts to study real-life policy influence on Twitter underline the importance of operationalizing influence in a way that actually can be said to measure an actor's impact on their surroundings. Cossu et al. (2015) study the relationship between Twitter influence and real-life influence. The authors conclude that examining Twitter data does not reveal which actors are influential in real-life communities. However, the study design differs significantly from that used in this study. Firstly, the authors describe that Twitter accounts used in their research are users 'annotated according to their perceived real-world (offline) influence' in 'automotive and banking domains'. The authors do not specify which type of actors are counted as real-life influential and how their influence is measured. Secondly, they have operationalized influence on Twitter mainly by looking at the influential actors' tweeting activity and the content of tweets. However, in earlier research, tweeting activity has not been seen to lead to the actor themselves being particularly central (Golder & Yardi, 2010). Instead, highly active network surroundings have been linked to being significant on Twitter (Cha et al., 2010; Kwak et al., 2010). Thus, an approach focusing on the surrounding network can better suit studying influence on the platform.

A few contributions within policy sciences have also studied influence on Twitter by investigating actors' centrality on the platform. Stier et al. (2018) studied policy actor influence in global Twitter networks and found that traditionally influential actors tend to occupy central positions even on Twitter. Although a notable finding, it does not suit well in explaining actor influence in local offline networks, as the study looks at tweets collected from global policy discussions on Twitter. The authors have also categorized political actors and media organizations as the 'traditionally influential' ones, making it impossible to distinguish between the two groups. Manor and Segev (2020) have attempted to study influence in an offline real-life network over Twitter. However, the authors measure centrality by looking at follower counts, which have in quantitative Twitter studies largely been seen to be an unreliable indicator of influence (Bakshy et al., 2011; Cha et al., 2010; Garcia et al., 2017; Romero et al., 2011; Wu et al., 2011; Yoon et al., 2022).

Most importantly for my study, the existing contributions have yet to address the question of whether the central actors in online networks are perceived as influential within the existing offline network. In earlier research, correspondence between Twitter centrality and policy influence has often been seen to follow from the reciprocal relationship between traditional media and social media (Chadwick, 2013). However, this notion assumes that actors that are visible in media would be the most influential in policymaking, which is not necessarily the case. Even though earlier researchers in other fields have convincingly shown that online networks provide a fitting proxy for offline ties, this relationship is yet to be fully explored in policy actor influence perceptions. As influence citations provide the most liable influence measure to date, seeing that there exists a relationship between being cited as influential and central on Twitter would confirm this relationship between online and offline influence more convincingly.

2.4.2. Popularity

In-degree centrality can thus describe the most influential actors within Twitter networks. However, merely observing which actors are centrally positioned does not say much about the mechanisms that have put the actor in that position in the first place. Looking closer at the influence construction process allows for examining the practical applications of an actor obtaining a central role. Such applications are, for example, how the central position reinforces the actor's influence and how the position is used in influencing others.

In statistical network research, the processes behind actor centrality are commonly studied with the help of preferential attachment or the so-called popularity effect (Barabási & Albert, 1999). Popularity is related to an actor's in-degree distribution, as it derives from the same phenomenon of an actor receiving incoming ties (Lusher et al., 2013). Measuring the popularity effect allows examining heterogeneities in actor centralities, i.e., how different actor or network characteristics affect an actor's ability to attract ties to themselves. Solely determining influence by high in-degree count treats influence more as an inherent actor characteristic, whereas accounting for the popularity effect corresponds better to the notion that this characteristic is based on a reputation constructed in interaction over time.

The most common popularity effect studied in network sciences is based on the theory of power law, according to which networks of all kinds tend to concentrate around high-capacity or high-popularity nodes (Barabási & Albert, 1999; Berardo & Scholz, 2010). This phenomenon is different network traditions called preferential attachment, popularity effect, or the 'rich get richer' principle. The effect denotes that the process of popularity is self-reinforcing so that an actor with desirable characteristics or resources can draw even more connections toward themselves (Lusher et al., 2013). The power law has been seen to create scale-free patterns in networks, meaning that regardless of network size, the low hierarchy nodes tend to link to the more widely recognized nodes (Barabási, 2009).

Earlier research shows varying evidence on popularity effect in tie formation within offline networks. Robins et al. (2012) show that preferential attachment did not affect tie formation in local governance networks. This result could imply, that the same would apply even in the climate policy network in this study. However, a contradictory result has been obtained by Hayes and Scott (2018). The authors find that popularity affects tie formation when measuring collaboration with an offline survey. However, the effect did not persist when the authors examined the online connections in between the same collaboration network actors. In a study on global Twitter networks on the other hand, Golder & Yardi (2010) found that the most connected actors could attract the most ties. This was concluded to be not because the prior connectedness had made them visible in the platform but because connecting to them was desirable due to their popular status (Golder & Yardi, 2010).

On Twitter, this capability to attract ties has been bolstered by connections from powerful partners. Retweets from global Twitter influencers such as celebrities, opinion leaders, and other elites have been seen to lead to an actor being more retweeted on Twitter (Bakshy et al., 2011; Shmargad, 2022; Wu et al., 2011). A powerful retweet can broadcast an actor’s tweets to a larger audience, thus providing an actor with a more structurally advantageous position on Twitter. This could be expected to be the case for Twitter interaction in between local policy networks, as a retweet from a real-life influential actor entails a signaling effect to the rest of the network.

In this thesis, I examine these two types of popularity effects, the ‘rich get richer’ effect (in continuation: popularity effect), and popularity conditional on retweets from powerful contacts. Both these effects give implications to the finding that an actor occupies a central role within a network. Firstly, the popularity effect illustrates that influencing on Twitter depends on users’ capacity to attract ties to themselves by their central status. This notion underlines that the influencing occurs through interaction in social media networks. Secondly, refining the effect by looking at ties from powerful real-life policy actors tests whether an influential actor’s influence extends to being able to affect the centrality of another actor. This expectation is based on the tendency found in policy networks, where connections to influential actors have been seen to lead to a structurally advantageous position in the network.

2.5. Summary

This thesis adds to policy networks literature by presenting a unique approach combining real-life influence perceptions to Twitter data. As presented in the first research question, the main aim of this study is to test whether influence citations indicate receiving ties on Twitter. Existing studies on influence in Twitter networks do not provide a strong enough foundation to claim that being central on Twitter would be directly related to being influential within the real-life policymaking network. Finding that influential policy actors occupy central positions in Twitter networks would offer policy network literature one of the first contributors showing that influence can be studied empirically with the help of social media data. To address the second research question, whether highly central actors can attract even more ties in the Twitter network, I test the popularity effect in the policy network on Twitter. The principle is widely examined in statistical network studies, but the pattern is yet to be tested amongst Twitter users in a real-life policymaking network. As for the third research question, I examine if being retweeted specifically by the structurally or formally influential actors in the real-life policy network bolsters this popularity effect. Earlier research on offline policy networks and Twitter networks has shown that powerful contacts can add to an actor’s influence. The effect has, however, not been examined quantitatively in online networks with retweets from offline policy network members.

3. The Finnish climate policy network

In Finland, politicians often pride themselves on the progressive climate policies that the country has been among the first countries to decide on. Such policies include founding the Ministry of Environment in 1983, enacting the so-called carbon tax in 1990, and passing the climate law in 2015. Despite this, Finland has fared notably lower in emissions mitigation than its peers (Koch & Fritz, 2014). In CO2 emissions per capita, Finland rates the highest amongst all Nordic states (World Bank, 2018), and in the Climate Change Performance Index (CCPI), Finland ranked in 14th place, with Sweden, Denmark, and Norway being at the top of the list[1] (CCPI, 2022). The status of a laggard rather than a leader in climate policy has been seen as odd for a progressive Nordic well-fare state. Finnish policymaking procedures are characterized by corporatist decision-making structures, an open political system, and a long tradition of coalition governments (Pelkonen, 2008; Vesa et al., 2018). In earlier research, these features have been seen to be determinators for pioneering in climate performance (Jänicke, 2005; Liefferink et al., 2009).

Hildén (2011) and Teräväinen (2010) have explained Finland's poor climate performance precisely by the corporatist and consensus-seeking institutional design. Hildén (2011) argues that during the early years of domestic climate policymaking, the processes were constrained by the low interest in exploring new innovations and re-evaluating policy problems and solutions when needed. According to Hildén (2011), presenting new innovations could lead to an' uncontrolled' process when a broad range of different interests are incorporated in the processes. As new initiatives need the approval of several actors to move further in the process, it can be difficult to arrive at policies that everyone can agree on. This notion is shared by Teräväinen (2010), that has described that the consensual and corporatist policymaking design has resulted in limited opportunities to change the prevalent policy discourse. Teräväinen (2010) argues that even though access to decision-making has been relatively open for a broad range of stakeholders, the

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[1] In the CCPI ranking, no country made it to the top three, which makes Sweden the fourth, Denmark the fifth, and Norway the sixth in the ranking.

consensus-seeking tradition lowers the responsiveness towards progressive environmental reforms. This leads to path dependency where new ideas are kept from even entering the table of possible policy measures.

More recently, Gronow and Ylä-Anttila, with partners, have studied actor influence in Finnish climate policymaking more closely. As the first part of the COMPON research project in Finland, the authors surveyed climate policy actors already in 2014. The results of their research show that the root cause for path dependency in policy has been the notably strong influence of actors that have prioritized economic goals over climate mitigation (Gronow et al., 2019; Gronow & Ylä-Anttila, 2019). The authors argue that a powerful coalition has been incorporated in the climate change policy system that has prioritized economic goals over climate mitigation (henceforth pro-economy actors).

This coalition consists of traditional tripartite organizations, i.e., business, trade, and industry representatives, as well as major political parties and ministries concerned with advancing economic growth and business objectives. The interest groups on the pro-economy side, such as business peaks and energy, forest, and agriculture industries, have enjoyed a privileged status in climate policymaking by obtaining close connections to vital governmental institutions. The strength of the pro-economy actors has also resulted in the relatively smaller impact of actors that have demanded more ambitious climate policies, such as the Ministry of Environment, climate research institutes, and environmental organizations (henceforth pro-climate actors)[2] (Gronow et al., 2019; Gronow & Ylä-Anttila, 2019).

Thus, the close relations between business and industry actors and central political institutes have been the key to understanding the outcomes of Finnish climate policies of the past decades. During the last few years, progress has been made as Finland has since 2019 declared to become carbon neutral as the first country in the world by 2035

[2] Gronow and Ylä-Anttila (2019) divide the policymaking field to three coalitions, Government and Reseach, Treadmill and NGO Coalition. The typology used in this thesis, the pro-economy and pro-climate, is not meant to refer directly to these coalitions, but to the general division in between actors that have been reserved towards or in favor of ambitious climate policies.

(Valtioneuvosto, 2019). However, reviews have shown that decisions made thus far are insufficient to reach the ambitious target (The Finnish Climate Change Panel, VN/16951/2020). This background calls for more research on the actor influence in the policy field, as the influence perceptions would yield more information on which interests are considered. During the rest of the chapter, I overview the three decades of Finnish climate policymaking. The chapter is not to be seen as a thorough account of all events in the Finnish climate policymaking arena but as an illustration of how the pro-economy and pro-climate sides have rivaled during formative policy events. Elaborating on the policymaking field during the past decades illustrates the prioritization of economic rather than environmental targets. It also sheds light on the prerequisites of Finnish climate policymaking of today.

3.1. International climate targets initiate national policymaking

Finnish climate policies are mainly formed by international cooperation within the United Nations Framework Convention for Climate Change (UNFCCC) and the European union. During the early years of domestic climate policymaking, issues were primarily brought to the agenda to meet requirements resulting from these international policy negotiations rather than having been initiated by national policymakers in the domestic arena (Hildén, 2011; Tirkkonen, 2000). The first mitigation targets for Finland were stated in the Kyoto Protocol in 1997 and the European union’s burden-sharing scheme. The first instance to lay out domestic climate policies was the Carbon Dioxide Committee, which was mandated to set Finnish emission reduction targets for international climate summits under the Ministry of Environment (Wilenius & Tirkkonen, 1998). The committee (later the Climate Committee) comprised representatives from several ministries, business and industry organizations, research institutes, and environmental organizations. Still, its decision-making was heavily influenced by the energy industry sector (Kerkkänen, 2010).

In the Kyoto Protocol, Finland committed to reducing its emissions below the level in 1990 by 2008-2012. After the treaty was completed, the climate change issue became more politicized. In the discussions that followed, the pro-economy and pro-climate sides started to form (Perimäki, 2002; Wilenius & Tirkkonen, 1998). The pro-economy side criticized the Finnish objectives in the treaty and argued that complying with the emissions reduction targets would be directly harmful to the Finnish economy. Even the government was divided in the question. Ministry of Trade and Industry (from 2008, the Ministry of Economy and Employment) and Ministry of Finance were highly against complying with the mitigation target.

In contrast, the Ministry of Environment defended it (Wilenius & Tirkkonen, 1998). On the pro-climate side, environmental organizations, climate researchers, the Green party and Ministry of Environment supported committing to the treaty's objectives. Finland met the Protocol's targets, and thus, the better-resourced and influential pro-economy did not get their views through (Perimäki, 2002). Considering that the obligations of the Kyoto protocol were relatively modest in the first place, it cannot be regarded as an enormous victory for the pro-climate side.

From the beginning of the 21st century, national climate policies have been outlined as national energy and climate strategies that have been drawn up once every parliamentary term. The drafting process involves several ministries, such as the Ministry of Environment, the Prime Minister’s office, the Ministry of Agriculture and Forestry, the Ministry of Finance, and the Ministry of Trade and Industry. A ministerial working group leads the work with representatives from all parties in the government. The main responsibility for coordination was assigned solely to the Ministry of Trade and Industry during the first years. The first strategies drafted in 2001, 2005, and 2008 were highly affected by the coordinating ministry's power, as they primarily concerned energy issues and hardly contained any assessment of policy impacts on the environment and climate (Kerkkänen, 2010). During the first years of climate policymaking, the division of labor in Finnish climate policies was an unusual one: Ministry of Environment was the main responsible for preparing national standpoints for international climate negotiations, but the most central ministry in domestic climate policies was the Ministry of Trade and Industry (Valtonen, 2013).

3.2. New visions in policy: the climate law and bioeconomy

In the 2010s, climate politics started to entail national policy visions instead of merely reacting to international demands (Hildén, 2011). During this time, the issue of climate started to become more mainstream, and climate policies were visible more frequently in

Finnish media (Lyytimäki & Tapio, 2009). New policy proposals were set to the climate change policy agenda after parliamentary elections in 2011 when the new government set legislating on climate law and founding an expert advisory body, the Finnish Climate Panel to the government program (Berg et al., 2014; Valtonen, 2013). The introduction of new pro-climate mitigation policies has been seen mainly due to the Green party and the Left Alliance obtaining seats in the government, which in earlier research has been seen to have led to more ambitious climate policies (Tobin, 2017).

During the first half of the 2010s, Finnish climate policymaking was characterized mainly by discussions on enacting the climate law. The Climate Change Act legislated in the United Kingdom (UK) in 2008 was used as an example. Environmental NGOs on the pro-climate side advocated for a strong law like the one in the UK with the campaign *Polttava kysymys* (‘the burning question’) as a part of The Big Ask campaign by the European Friends of the Earth. According to Torney (2019), the industry lobby highly affected the preparation process. The pro-climate side constantly had to accommodate and lower their targets even to get some of their policies through. In the end, the climate law was set to be a legal framework that would establish a statutory planning and monitoring scheme for climate policymaking. The law broadened different interest groups’ and authorities’ participation in policymaking and, most notably, set the aim of reducing emissions by 80 percent from the level in 1990 by 2050 into the legislation. However, the law ended up not entailing several of the elements that the pro-climate side had advocated for, such as the mid-term targets or ‘carbon budgets’ as it was decided on in the UK (Pölönen, 2014).

The Ministry of Environment was the only ministry advocating for a strong climate law, whereas the Ministries of Finance, Employment and Economy, and Agriculture and Forestry were against (Torney, 2019). During the preparations of the legislation, it was discussed which ministry would be mainly responsible for coordinating and planning policies under the framework of climate law. The Ministry of Employment and Economy wished to keep its pre-existing status as central coordinator, whereas the Ministry of the Environment wanted to gain more responsibility in policymaking. As a compromise, it was stated that the Ministry of Environment would compile medium-term policy plans (periodically once in every parliamentary term), and the Ministry of Employment and Economy would draft long-term plans (once every ten years). The Ministry of

Employment and Economy obtained its old task of compiling energy and climate reports, which means that climate strategies are now drafted parallelly in two ministries, (Torney, 2019).

In 2013, the national energy and climate strategy noted for the first time that Finland's long-term goal was to reach carbon neutrality (Ministry of Economic Affairs and Employment, 2013). However, the preceding government that took office in 2015 did not comply with this goal. The energy and climate strategy published in 2016 stated that Finland would increase the use of renewable energy by expanding the share of forest biomass as an energy source. The plans entailed significant growth in forest logging, a measure largely supported by the forest and agriculture industry (Hakkila, 2006). Independent impact assessments estimated already in 2017 that due to the increase in wood burning and use of biofuels, Finland's net emissions would not decrease by the year 2030 (Koljonen et al., 2017). This would be mainly due to the increased need for forest logging, reducing the Finnish carbon sinks. Kivimaa and Mickwitz (2010) have argued that biofuels being a fossil-free energy source, they have been framed as a solution to adapting energy production to mitigation targets even though it is widely known that they also contain negative impacts on the environment. The pro-climate side criticized the government for focusing almost exclusively on biomass as the solution to fossil-free energy production as the only country in Europe (Ollikainen, 2017).

3.3. The 'pro-mitigation' shift

During the year 2018, a global interest in climate issues could be seen. The youth climate movement Fridays For Future, launched by Greta Thunberg in the Fall of 2018, increased the prevalence of climate on the public agenda. The release of the widely acknowledged IPCC special report *Global Warming of 1.5 ºC* in October of 2018 has been seen to be a motion-setting power in the issue of climate change becoming mainstream in political discussions. The government's initial response to the IPCC report release was reserved in Finland. On the day of the release, the Environmental Minister from the Center party commented that tightening Finnish climate objectives to meet the demands for limiting global warming to 1.5 Celsius was 'not possible during the upcoming months' (Eskonen & Koistinen, 2018). However, in December 2018, all parties in the parliament gathered in round table discussions on joint climate strategies for the upcoming years. Eight parties in the parliament drafted a joint statement stating, ‘The climate policies of the European Union and Finland will be renewed so that we can do our part to limit the global mean temperature increase to 1.5 degrees’ (Valtioneuvosto, 2018).

The years 2018-2019 mark a period of citizen mobilization in climate issues never seen before in Finland. A total of four large demonstrations took place within a period of a year: two climate marches by a coalition of Finnish NGOs in October 2018 and April 2019 and two school strikes organized by the Fridays for Future youth movement in March 2019 and September 2019. Before the upcoming parliamentary elections in April 2019, nine Finnish environmental NGOs launched the campaign Korvaamaton (‘Irreplaceable’) to raise the climate visibly to the agenda during the elections campaigning. Due to the broad mobilization of the climate issue, the parliamentary elections in 2019 were frequently described as ‘climate elections. In the following analyses, the climate was brought up as one of the most important themes of (Borg et al., 2020). That two parties with ambitious climate policies, the Green League and the Left Alliance, managed to improve their performance in the elections was also seen as an indicator of the prevalence of the climate issue in election campaigning (Ibid.).

In the program of the green-leftist government taking office in 2019, it was stated that Finland would aim to become emissions-neutral by 2035 as the first country in the world. During the preceding right-wing government, the emissions neutrality goal was set to 2045, meaning that the new target entails a significant ramp-up to the ambition level in climate policy. The new government consisted of Social Democrats as the Prime Minister party, the Green League, Left Alliance, the Swedish People’s party, and the Center party. As the Social Democratic party is the biggest party in the parliament and the party emphasized the issue of climate also during the elections (Borg et al., 2020), it would seem possible that the party has in climate issues at least temporally changed side from the pro-economy to pro-climate.

Despite the ambitious policy outline, several research institutes and the Finnish Climate Change Panel concluded unanimously in February of 2022 that the decided measures are insufficient to reach the stated mitigation goals (The Finnish Climate Change Panel, VN/16951/2020). The government’s incapability to decide on effective mitigation measures for more difficult issues such as forest logging, peat burning, and traffic has been seen to result from the government parties highly disagreeing on the level of ambition (Koistinen, 2020). The government, including both the pro-climate Green party and the pro-economy Center party, has large differing views on how parties position themselves with ambitious climate policies (Savolainen & Ylä-Anttila, 2021). The target of carbon neutrality has also suffered major setbacks by the reviews showing that the extensive loggings during the past years have resulted in a notable reduction in Finland's carbon sinks (Luke, 2022). It remains to be seen whether Finland can change the course of climate policies and become a leader in setting and achieving targets.

4. Data description and method

4.1. Constructing the Finnish climate policy network

The data used in this thesis has been collected as a part of the COMPON research project (Comparing Climate Change Policy Networks) at University of Helsinki. The network identification and data collection have been conducted by the COMPON research team. The further processing of the collected data and the analysis is done by the author[3]. Identifying network members is an especially critical task in network analysis, as missing links in the policy network pose severe threats to the reliability of the results (Berardo et al., 2020). Missing links between important actors could be crucial to the conclusions drawn from the overall structure of the network. Networks are usually identified by the nominalist or the realist approach or a combination of both (Laumann et al., 1989). The nominalist approach relies on the researchers' perceptions and summoned expertise about the relevant actors in the policy field. The realist approach is often conducted as the so-called snowballing technique, where some first identified network members nominate more actors that should be counted in the network.

The members of the Finnish climate policy network were identified by combining the nominalist and realist approaches. The COMPON researcher team's views on relevant actors were complemented by consulting climate policy experts and examining printed media sources (Ylä-Anttila et al., 2018). This process resulted in a roster of 104 organizations representing different sectors of society: governmental, scientific, business, and civil society organizations. After identifying the relevant actors, information about the relationships between them can be collected. For this thesis, I use two separate data sets that contain connections between the same climate policy network actors. Firstly, I use the influence survey data collected from the network organizations themselves, and secondly, retweet behavior data collected from Twitter. Both data sets are organized as so-called edgelists. Every row in the two sets represents a connection (or edge or tie)

[3] The author is solely responsible for any eventual errors in the data.

between two actors (or nodes): the sender (ego) sending a connecting the receiver (alter). The connection in the influence survey data is the influence citation from the ego to alter, and in the Twitter data the retweet from ego to alter.

4.1.1. Influence survey data

The perceived offline influence consists of online survey answers collected from the members of the climate policy network in December 2020. In the survey, the respondents were presented with a roster of all 104 climate policy network actors and asked to indicate which actors they find especially influential in domestic climate change politics[4]. To maximize the response rate, the respondents were contacted by phone in advance. They also received several reminders to answer the online survey. The form was designed carefully and made as short as possible to avoid respondent fatigue. 89 of all 104 actors responded to the study, resulting in a response rate of 85.6 percent. For survey-based research in general, this would be considered an exceptionally high response rate. In network sciences, however, a large share of non-respondents can affect the validity of the results. In network studies where surveys are used to map actual communication and collaboration patterns within the network, missing links between key actors can pose a severe risk to the applicability of the results. Even in the case of this study, a few essential actors omitted to respond to the survey, such as the Prime Minister Party Social Democrats, the Ministry of Finance, and the Finnish Climate Change Panel. It should also be noted that the most climate-skeptic party in the parliament, the Finns party, did not take the survey.

In the case of this thesis, it can be estimated that the absence of contributions from these actors does not affect the influence of each actor and that the response rate is sufficient for getting reliable results. The influence survey data is not used as the modeled network in the analysis but to form the actor-level trait of perceived influence. Therefore, missing citations do not significantly distort the relationships between actors. The non-responding

[4] The question in Finnish: ”Mitkä organisaatiot ovat mielestänne erityisen vaikutusvaltaisia suomalaisessa ilmastopolitiikassa?” (Translation: Which organizations do you find as especially influential in Finnish climate policies?)

organizations were still included in the roster of policy network actors and could be cited as influential by the other organizations. Moreover, the group of non-respondents consists relatively equally of different types of organizations: five are governmental, three are scientific, four are business, and three are civil society organizations. As the vast majority contributed to the survey, it is rather unlikely that actors' influence citations would be highly affected by some organizations' absence. For further details on the network identification and data collection procedure in the COMPON research project, see Ylä-Anttila et al. (2018).

4.1.2. Twitter data

The retweet data forms the online network that is modeled in the analysis. The data was collected using Twitter's application programming interface (API) in December 2021. The data collection protocol is fully elaborated in Chen et al. (2021a) and the GitHub repository[5]. The author contributed to processing the primary data and developing the protocol together within the COMPON research group. The protocol is now used across several studies on Twitter climate policy discussions. Further processing of the data for this thesis was conducted in the programming environment R Studio with the help of the 'statnet' and 'ermg' packages developed for network data (Handcock et al., 2008, 2010). The code used to process the data and conduct the ERGM analysis is presented in Appendix A.

The data consists of retweets between organizations in the climate policy network during 2018-2021[6]. Besides the connections, the data contains information on the retweet handle, retweeted tweet, organizational affiliation, level of the user, type of organization, and exact time of the retweet. Amongst the collected users were the official Twitter accounts of the climate policy network organizations and the accounts of individuals that represent the organization. This is motivated by how political and societal elites use their personal accounts to participate in policy discussions (Hemphill et al., 2013). Including a broader

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[5] Link to the GitHub repository of the project: https://github.com/tedhchen/componMultilayer

[6] The data collection was done in the middle of December 2021. As the last month does not contain the full retweet activity, it will not be included in the ERGM analysis.

range of accounts makes it possible to capture different types of behavior, which adds to the value of using Twitter instead of only survey data in determining actor influence. For most of the organizations in the data, it can be expected that the top leaders' and sub-units' tweeting behavior is aligned with the organization's views. Thus, adding their retweets to the sample is well justified.

In the data, each network organization has three types of Twitter users accounted to them: (1) the organization’s main Twitter account, (2) the personal Twitter accounts of the organization’s top executive leaders, and (3) the organization’s sub-divisions’ Twitter accounts, if applicable. The official Twitter accounts for the respective organization were identified by searching on Twitter, Google, or the organizations’ web pages. For every actor, there is only one organizational main account. The top executive leaders of each organization were identified by manually searching on the network organizations’ web pages and social media service LinkedIn. The Twitter accounts could be found on these same pages or by searching by the individual’s name on Twitter. As top executives were counted main chief personnel that, according to their title or work description, had decision-making power for the whole organization, i.e., belonged to the executive management team. As an exception to this rule, all members of the Finnish parliament and Finnish Members of the European Parliament (MEPs) were included as representatives for their parties. The democratically chosen parliament is the highest decision-making body in Finland, and Finnish MEPs are often long-term politicians with authority also in domestic policies. Thus, they are included to account for all notable political leaders in public policymaking.

The third category of accounts, organization sub-division accounts, applies to larger organizations with sub-units with their own Twitter pages. Examples of such sub-divisions are university departments or political parties’ party newspapers. A specific protocol was conducted for the collection of these accounts. Firstly, the account had to follow the official main Twitter account of the organization, and secondly, also be followed back by the main account. Thirdly, the account had to have a specific keyword in the Twitter bio text. The keywords were accommodated for each individual organization separately, and they usually contained variations of the organization's name and other organization-specific words and phrases. For example, in the case of Fridays for Future, the keywords were ‘fridays for future’, ‘fff’, ‘ilmastolakko’, ‘climate strike’, ‘koululakko’, and ‘school strike’. These first three steps were carried out by a Python code that extracted all Twitter accounts and their bios that fulfilled the three conditions. Fourthly and lastly, a research assistant went manually through the extracted lists and marked all accounts that could be assessed as subunits to the main organization based on the account name and bio text.

To focus on climate change policy-related discussions, the tweet corpus was narrowed down to tweets containing specific keywords that are often used in conversations about climate and environment. The list of keywords is presented in Appendix B. The list of keywords was conducted based on knowledge of Finnish climate policy discourse on Twitter in consultations with the COMPON research group members. The list includes 332 climate and environment-related expressions or phrases in Finnish, Swedish, and English. Not all terms are directly related to climate or environmental issues, but they are a part of the multiplex field of climate mitigation measures. To ensure that the expressions not directly tied to climate were indeed used in the climate policy context, the author made a manual check of Tweets samples. If the inclusion of the term resulted in a notable amount of non-climate related tweets, it was excluded from the final list. This check excluded some words, but most of the listed terms were accepted as they were used with references to climate or the environment. However, as the list includes 332[7] different words or expressions, manually going through every single keyword was not possible or even functional for the study.

After deleting tweets where users retweet their own content, the final data set comprised 70 883 retweets between 1016 Twitter accounts. For the statistical analysis, the tweet corpus was turned into a more simplified network form to get interpretable results from the exponential random graph modeling. Firstly, the three types of accounts collected for each organization were merged into one network node. Thus, in the analysis, all the retweets are treated as if they were sent between the 104 network organizations, despite

[7] As this number includes the different inflections used in Finnish and the translations to English and Swedish, the actual number of topics covered by the keywords is significantly lower.

which individual accounts they were sent from and targeted to in the first place. With this modification, retweets between two accounts with the same organizational affiliation are counted as self-ties and omitted from the analysis.

Secondly, the data was divided into periods of one month. Each of these monthly periods was then formed into a network, resulting in 48 networks. The size of one month was chosen as retweets from one month could yield networks with a sufficient amount of connections for the ERGMs to estimate. On the other hand, an even longer period would be unable to capture the activity peaks that evolve around different events in the policymaking field. Moreover, in the analysis, research questions two and three, concerned with the popularity effect and the impact of influential retweets, are operationalized by looking at retweets during the previous month in the timeline. Tweets further away in the past than a month ago would be difficult to argue to be highly related to an actor's centrality. As two actors can be tied to each other with only one edge in a network, duplicate ties between two network organizations were deleted each month. All connections are treated as equal in the analysis, despite whether there originally has been several or only one edge between the organizations.

Lastly, in the analysis, each month is modeled separately with the help of ERGMs. This approach gives more meaningful results than modeling the total Twitter data as one network. Twitter communications change rapidly and are highly dependent on the overall policy discussion climate context. Dividing the data into networks representing a calendar month allows comparison between different phases in climate policymaking. In a more extensive network, data aggregation could also affect some of the results as the likelihood of certain types of ties occurring increases. Inspecting monthly networks gives a more realistic picture of the actual discussion dynamics. Seeing that the hypothesized effects persist for a longer period also strengthens the robustness of the results.

As regards to ethical concerns and data privacy, the studied organizations and individuals have not been asked for permission whether they wish their Twitter data to be used in the analysis. This would not be feasible due to the large number of users included in the data, nor is it even congruent with the customs of open-source data research. All data used in the study has been collected from public Twitter accounts, meaning that the relationships and affiliations can be observed by anyone with access to the Internet. In the descriptive analysis section, I will only present the activity of prevalent Twitter users subject to public scrutiny due to their societal status. Furthermore, the results of ERGM modeling will only be presented on a general level, not by individual organizations.

4.2. Descriptive analysis

The offline survey network. The offline influence data can also be constructed as a network, influence citations representing directed ties between the climate policy actors. After discarding self-ties (edges where organizations cite themselves as influential), the influence network contains a total of 3 389 edges. With 104 organizations in the network as receivers, the density of the network is 0.32.[8] Table 1 shows the top 20 organizations cited as the most influential in the survey. An actor's influence is determined by the in-degree measure as the sum of incoming ties in the network. The highest amount of possible influence citations is 88, the respondent rate of 89 minus one.

The top of the list consists mainly of the pro-economy governmental and business sector actors. This aligns with the description of the Finnish climate policy network made in chapter 3 that the pro-economy side has primarily dominated the climate policy decision-making field for decades. It is noteworthy that most influential organization is the Ministry of Environment from the pro-climate side. In the influence survey conducted in 2014, the Ministry of Employment and Economy was the single most influential actor (Gronow & Ylä-Anttila, 2019). This could be seen as a result of the climate law that entered into force in 2015, which increased the authority of the Ministry of Climate in domestic climate policies. It could also mean that the pro-climate side has strengthened their position in the decision-making procedures, as the government constellation includes green-leftist parties.

[8] As the data lacks out-edges from 15 organizations, the density is assumably underestimated.

Top 20 organizations most influential offline	Type	In-degree
Ministry of Environment	GOV	76
Ministry of Employment and the Economy	GOV	72
Confederation of Finnish Industries (EK)	BUS	71
Ministry of Finance	GOV	69
The Finnish Climate Change Panel	SCI	68
Energy Industries Federation	BUS	67
Ministry of Transport and Communications	GOV	66
Ministry of Agriculture and Forestry	GOV	66
Sitra	CIV	66
Fortum Corporation	BUS	65
Center Party	GOV	64
Social Democratic Party	GOV	63
National Coalition Party	GOV	62
Forest Industries Federation	BUS	62
Green Party	GOV	62
Neste Corporation	BUS	59
WWF	CIV	59
Finnish Association for Nature Conservation	CIV	58
Prime Minister's Office	GOV	58
Central Union of Agricultural Producers and Forest Owners	BUS	56
Finnish Environment Institute	SCI	55
Finnish Meteorological Institute	SCI	54

Table 1. Top 20 organizations by their actor in-degree centrality, 88 being the highest number possible. GOV = governmental and political actors, SCI = research and scientific organizations, BUS = business and industry organizations, and CIV = civil society and labor organizations.

The online retweet network. The total retweet activity between all accounts within each month can be examined qualitatively as it gives more insight into the discussions on the policy arena during the study period. The total activity varies between 823 to 2 343 climate-related retweets per month. The average monthly activity is 1477 retweets, and the activity median is 1487. When accounts are merged and duplicate ties are omitted, the number of network edges within each monthly network varies between 180-464. The average network size is 312 edges, and the median is 317. The total activity being much higher than the networks illustrates that as could be expected, users tend to retweet others with the same organizational affiliation and the same actors frequently within one month. After deleting merging nodes and removing duplicate ties, Twitter network density for each period is relatively low and varies in between 0,043-0,016. As density gives the ratio between observed ties to the number of possible ties, only a few percent of possible retweets between different network actors occur monthly between the network members. The scarcity of connections can be seen as a strengthening argument for using retweets as a sign of endorsement, as actors choose with careful consideration whom they retweet from other organizations.

The Ministry of Environment is also the most retweeted actor within the policy network. This adds to the face validity of my study and gives preliminary support to the notion that the most influential policy actors can be identified in Twitter networks. The list of most influential actors on Twitter seems rather pro-climate. The Green party has several representatives in the list with the most retweeted actors. More research institutes and universities are at the top of the list than in the influence survey list. The list lacks the big political parties, National Coalition, Social Democrats, and the Center Party, nor are any traditional energy and business organizations included. This can be seen as unsurprising, as climate change policymaking is only one part of their activities. For many other users on the list, climate change is the most critical policy issue. The total amount of retweets received by the 20 most retweeted Twitter users during the study period is 25 646. The number accounting for roughly a third of all received retweets in the data indicates that the network concentrates around highly popular nodes.

Comparing the two lists gives insight into the differences between the two ways of measuring influence. The central Twitter actors are also organizations that observers of climate policymaking would hold as influential. The fact that Twitter network is more pro-climate would support the expectations laid out in the research questions, that the popularity effect and powerful contacts contribute to tie formation in the network. It would seem likely, that most influential users have obtained their status due to preferential attachment, their popularity being constructed by being highly retweeted in the pro-climate Twitter discourse. The pro-economy actors would seem to be in a disadvantaged position in the discussions, as their side does not have strong policy advocates that could occupy central roles in Twitter discussions.

Correlation tests between the organization’s total in-degree measures in the influence survey and Twitter networks show a moderately strong positive correlation between receiving ties in the influence survey and Twitter. Pearson’s correlation coefficient is 0.48, and Spearman’s rank correlation is 0.51. The Spearman’s rank correlation test showing a slightly stronger relationship illustrates that the relationship is not entirely linear. Knowing that the top 20 Twitter accounts amongst 1016 users receive over a third of all sent retweets, it would be expected that the relationship is monotonic.

Most retweeted	**Organization**	**Type**	**Indeg.**
yministerio	Ministry of Environment	GOV	2528
maripantsar	SITRA	CIV	2130
sykeinfo	Finnish Environment Institute	SCI	2102
lukefinland	Natural Resources Institute Finland	SCI	2081
mikkonenkrista	Ministry of Environment & Green Party	GOV	1782
helsinkiuni	University of Helsinki	SCI	1678
tem_uutiset	Ministry of Economy and Employment	GOV	1365
luonnonsuojelu	The Finnish Association for Nature Conservation	CIV	1215
mmm_fi	Ministry of Agriculture and Forestry	GOV	1185
hiilineutraali	Finnish Environment Institute	CIV & GOV[9]	1124
sitrafund	SITRA	CIV	1121
motivaoy	Motiva	BUS	1033
ilmatiede	Finnish Meteorological Institute	SCI	911
liisarohweder	WWF	CIV	881
vihreat	Green Party	GOV	881
lvmfi	Ministry of Transport and Communications	GOV	850
valtioneuvosto	Prime Minister’s Office	GOV	782
mariaohisalo	Green Party	GOV	733
satuhassi	Green Party	GOV	634
aaltouniversity	Aalto University	SCI	630

Table 2. The most retweeted Twitter accounts in the Twitter data by their total in-degree in 2018-2021.

Twitter activity. Figure 1 illustrates the fluctuation in total activity on Twitter per period. The plot shows that the network activity peaks during notable events within the climate policy arena. The first high spike occurred in October 2018, when the broadly acknowledged IPCC 1.5 °C special report was released, and the first large climate demonstration was organized. The two highest peaks in the plot denote the two significant

[9] Hiilineutraali (‘carbonneutral’) is a Twitter page of the Finnish Environment Institute (SYKE). SYKE uses the Twitter page also for communications about the Towards Carbon Neutral Municipalities (HINKU) -network which can be classified as a governmental actor.

School Strikes for Climate organized by Fridays for Future in March 2019 and September 2019. The activity also peaks at the government's annual budget summits in September 2020 and 2021, when the government had difficulties in finding consensus on climate policies. The last spike in the plot denotes the UN Climate Change Conference COP26 held in November 2021. The activity drops in the holiday seasons during the summer and Christmas months. The figure shows that the online Twitter discussions follow the 'offline' policy discourse, as the retweeting peaks during several periods when climate change policies were up on the political debate. This strengthens the argument that Twitter is useful for studying policy interactions.

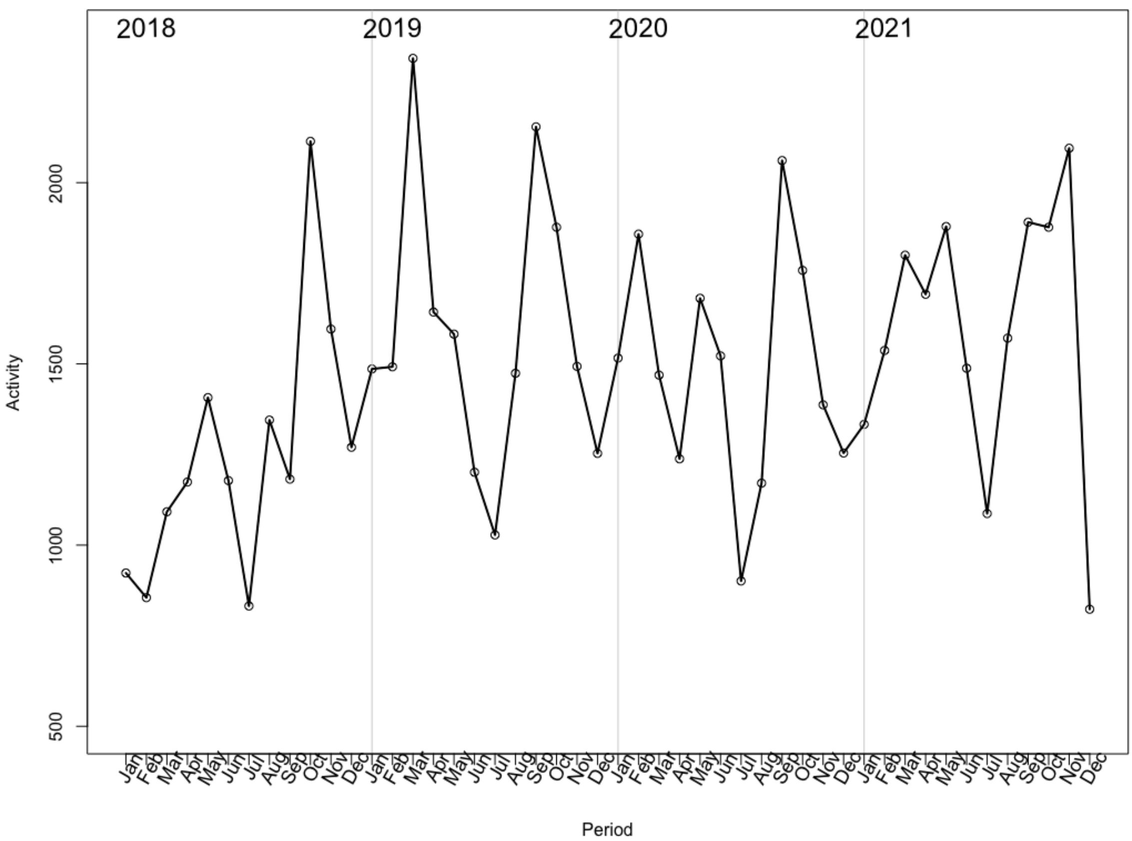

Figure 1. The total retweet activity for each month.

4.3. Exponential random graph modeling (ERGM)

I model the Twitter network with the help of exponential random graph modeling (ERGM), a statistical tool used to explore patterns for tie formation in social networks. ERGMs, first introduced in their fully specified form by Wasserman and Pattisson (1996), are a family of statistical models used in network research to draw statistical inferences on relations between actors within social networks. With the help of statistical modeling researchers can explore random properties of actors and relationships between them within a particular network (Wasserman & Pattison, 1996). The observed network, that is, the network as it has been collected in the data, is assumed to be a result of an unknown, stochastic process. ERGMs allow revealing this process by testing theoretically motivated and plausible factors that can be seen to have affected the observed network structure (Lusher et al., 2013).

An ERGM is specified as the probability function

$$\Pr\,(Y = y) = \left(\frac{1}{\kappa}\right)\, exp\left\{\sum_{A} \eta \mathrm{A} \delta \mathrm{A}(\mathrm{y})\right\}$$

Where A is a type of network configuration, ηA is the parameter term, δA(y) is the network statistic, and κ is a normalizing constant that ensures interpretable results and that the probability model sums to 1 (Lusher et al., 2013). The model gives a general probability distribution of observing a network *y*, which depends both on the statistics δA(y) in the network, and on the different non-zero parameters ηA for all configurations A in the model (Robins et al., 2007).

In ERGMs, the unit of analysis is a dyad. A dyad is formed by two nodes connected with a network tie, and the model estimates the likelihood of the dyad taking place in the network. ERGMs are designed particularly for modeling social relations. Analyzing social networks with more traditional statistical approaches, such as OLS regression, would inherently violate one of their fundamental principles, that of independence of model variables. In the study of social relations, the overall structure of the social community itself has a significant impact on forming individual ties within it. This notion can be illustrated with an intuitive example of friendship between Mary, Peter, and John.

Knowing that Mary is friends with Peter and John increases the likelihood of Peter and John being friends, in comparison to a situation where Peter and John would not have a common acquaintance (Lusher et al. 2013). Thus, when estimating the likelihood of Peter and John forming a tie, the effect of being friends with Mary needs to be accounted for.

Advantageous in using ERGMs is their capability to account for both actor-level effects (for example, that Peter and John both are of the same gender) while simultaneously taking into account the overall network structure and dependencies that social relations often entail (for example, that Peter and John both are friends with Mary). These two types of effects are commonly referred to as exogenous and endogenous in the network literature. These endogenous effects, or as commonly referred to, local network configurations, are included in ERGMs to capture global behavioral tendencies that occur in the data more often than would be expected by chance (Cranmer & Desmarais, 2011). In the Finnish climate policy network, an expected configuration would be the 'k-star' configuration, which captures the tendency for popular actors to receive more ties in the network.

The ERGMs are fitted via Markov Chain Monte Carlo Maximum Likelihood Estimation (MCMC MLE) (Lusher et al., 2013). The MCMC procedure simulates a sequence of network statistics by incrementally making small changes to the simulated networks. Moving from the current network to a new one, the simulation randomly chooses a pair of nodes and removes or adds a tie, depending on if the two nodes are already tied. If changing the edge makes the network more likely to be observed than the previous one, the new network is added to the sequence, and the simulation continues. The log-likelihood of the ERGM is evaluated iteratively until the estimation procedure converges, i.e., reaches sufficiently close parameter values to the observed network (Ibid.) The dependent variable is the log odds of a tie forming; the model output can be interpreted the same way as logit regression results. Thus, the model coefficients denote, the change in log odds given an increase of one unit in the model term, conditional on all other modeled effects.

A common problem with ERGMs is degeneracy in model estimation. Trying to fit models that do not explain the underlying structure of the network sufficiently well can lead to model degeneracy (Cranmer & Desmarais, 2011). A degenerating model means that the model estimates there to exist only one of a few possible network structures, often an extreme network with all possible edges or no edges at all. A degenerated model does not give any interpretable results and indicates a poor fit to the data. To avoid degeneracy problems, ERGMs need to be carefully specified for the model to estimate. This means that, as opposed to regression modeling, the models cannot include a set of ‘standard controls’ that do not contribute to the model's explanatory power. On the other hand, ERGMs often need to include most of the essential model variables for the estimation to start in the first place. As argued by Cranmer and Desmarais (2011), this ‘weakness’ of model degeneracy means that ERGMs simply need to fit well into the data they are modeling, which is not an unreasonable demand for a statistical model to begin with.

ERGMs are fitting for answering the stated research questions in this thesis as they allow investigating of the reasons behind actors’ central positions. The tie-oriented approach is justified by the assumption made in this thesis that social structures rather than inherent actor characteristics are the key source of influence in policy networks (Ingold et al., 2021). Moreover, measuring influence by observing in-degree in networks, as shown in tables 1 and 2, could give misleading indicators for actors’ overall impact. An actor having a high in-degree could be due to the actor being a central figure in a tightly formed cluster, even though they would not be connected to other groups in the overall network. For example, environmental NGOs tend to retweet each other’s activities on Twitter to gain visibility for their advocacy work. However, to gain influence, their tweets need to gain a wider audience amongst the network participants.

4.4. Model specification

In this thesis, I develop ERGMs for the Twitter network amongst the climate policy network members. Altogether, four ERGMs are fitted separately for the 46[10] periods of monthly networks to test if the factors presented above contribute to an actor being central on Twitter. The posed research questions are answered by including five focus effects:

[10] The first period, January of 2018 functions as a baseline period in the timeline analysis and is thus omitted from the analysis. Also December 2021 is omitted as the data only contains the first two weeks of activity.

the effect of being influential (influence effect) or a governmental actor (government effect), receiving ties in general (popularity effect), receiving ties from influential actors (influence in-degree effect) or receiving ties from governmental actors (governmental in-degree effect). In addition, I also include a set of other effects to account for other factors that might contribute to ties forming in the network.

The influence effect. To answer the first research question, ‘are influential actors central on Twitter’, I assigned every node their influence score based on how many times they have been cited as influential in the influence network. The score is counted as the in-degree centrality, i.e., a simple sum of incoming ties, normalized to take a value between 0 and 1, 1 representing the maximum value of citations.

The governmental effect. As for the second influence measure, I include a node covariate to account for governmental actors receiving more ties in the network. Governmental actors are ministries, governmental agencies, political parties, and cities[11]. The covariate is assigned as a dummy variable, where the node takes value 1 if it is a governmental actor and 0 if not.

The popularity effect. With the second research question, I investigate if ties beget more ties. The parameter for the popularity effect is constructed by assigning the nodes their in-degree centrality in the Twitter network for t-1, i.e., the total sum of incoming ties during the previous period. For example, an actor’s popularity effect for period two (t_2) is determined by the in-degree centrality measure in period one (t_1). For the results not to solely confirm the rather trivial finding that the actors that are the most retweeted ones in the past are the most retweeted ones in the future, an edge covariate term is added to control for tie formation in the previous period.

The influence in-degree effect. With the third research question, I set out to examine if ties specifically from influential actors matter for an actor being more central in the Twitter network. I control for incoming connections from influential actors by utilizing

[11] Cities that have been identified to be a part of the climate policy network are Helsinki, Tampere and Turku.

the influence score of each actor. As with the popularity term explained above, the influence in-degree term is constructed by summing up all incoming ties during the previous period. This time, each tie is weighed by the influence score of the sender. The higher the influence in-degree measure for the previous period, the bigger the effect of influential ties to tie formation in the present period.

The governmental in-degree effect. Lastly, I investigate whether ties from governmental actors contribute to an actor receiving more ties on Twitter. The term is constructed analogously to the popularity term, only this time, solely ties from governmental actors are counted. Thus, the governmental in-degree term consists simply of the sum of ties from governmental actors during the previous period.

Additional baseline model effects. To account for other effects that can contribute to tie formation in the networks, I add several other effects in the baseline model. I first include the homophily term to account for one of the most common contributors to ties being formed, similarities between organization types (Goodreau et al., 2009; Gu et al., 2014; Mousavi & Gu, 2015). There are four organization homophily parameters: governmental, scientific, business, and civil society. The term takes the value 1 if both actors are of the same type of organization and 0 if they are not. Secondly, I add a past network edge covariate to control for incoming edges in the past network period. This is to make sure that the in-degree terms do not solely show that actors tend to be retweeted by the same organizations, but that they instead capture whether A retweeting B affects C retweeting B.

Thirdly, I include four endogenous network effects common to ERGMs. The edges-term controls for the baseline probability of ties forming in the network. The mutual-term accounts for the tendency of ties to be reciprocated. I also include a commonly used network configuration to capture the heterogeneity in popularity in the modeled network, the geometrically weighed in-degree term (GWI-degree) (Snijders et al., 2006). The parameter captures a similar tendency as that of the popularity effect explained above but uses incoming ties in the modeled network instead of the preceding network. Lastly, the geometrically weighed edgewise shared partner (GWESP) term captures the well-documented phenomenon of transitivity in social networks, i.e., the ‘a friend of a friend is a friend’ effect. (Snijders et al., 2006).

In developing the models for this thesis, I experimented with various node and network-level variables that could contribute to tie formation. As node-level covariates, I tested all the different actor groups in the data (governmental, scientific, business, and civil society organizations) in examining whether actor type is related to receiving more ties. I also tested the effect of incoming connections from these actor groups similarly to the influence and governmental in-degree terms. As network-level variables, I included the geometrically weighed outdegree term that accounts for activity, i.e., a node sending more ties than nodes on average within the network. These terms did not contribute to a good fit in the data, which is why they were omitted from the analysis.

5. Results

5.1. Influence and government effect

The model fitting is done by starting with a baseline model and gradually adding higher degree terms. The baseline model includes only the lower degree node level terms and network configurations that have proven vital for the models to estimate. Then, by adding higher-level terms one by one, I can test whether the hypothesized effects improve the model's explanatory power. Each new model is tested against the previous, lower-rank model to see whether the added term has improved the model fit. As the model parameters contain high interdependencies with each other, considering changes in the whole model as opposed to only looking at the specific coefficient is necessary for an adequate interpretation of the results (Lusher et al., 2013).

I begin by fitting the baseline model (model 1) that includes all other model terms explained above, except for the popularity effect, influential in-degree, and governmental in-degree terms. In the first model, I look at the node level effects as stated in the first research question, whether influence affects tie formation on Twitter. Model (1) output for the influence and government effects are plotted in Figure 3. The plots give the term coefficients and *p*-values for the node covariates in each monthly network. The green color indicates that the term is statistically significant with $\alpha = 0.05$ level, red color indicates non-significance. A coefficient above zero indicates that the effect is positive, and under zero means that the covariate has a negative impact on receiving ties in the network.

Of the two node covariates, the influence attribution is positive and statistically significant in all networks. Thus, the results show a robust positive effect of being perceived as influential in the policy network to receiving more ties in the Twitter network. The coefficient for the effect of being a governmental actor is mostly insignificant, and the parameter varies between positive and negative. Being a governmental actor and obtaining formal powers does not seem to mean much for popularity on Twitter. This discrepancy in the two influence measures aligns with the argument made in the theory section that the reputation of being influential matters in inter-organizational relationships.

However, this finding can be interpreted to merely show that not all representatives of the governmental system are perceived to be particularly powerful in climate policy, neither measured by their perceived influence nor Twitter centrality. This notion is in line with the results presented in table 1, in which the list of the 20 most influential actors consists of only by roughly half of the governmental actors. Since influential actors are more likely to receive ties in the network than other actors, the results support a positive answer to the first research question, whether influential actors in the policy network are central to the Twitter network.

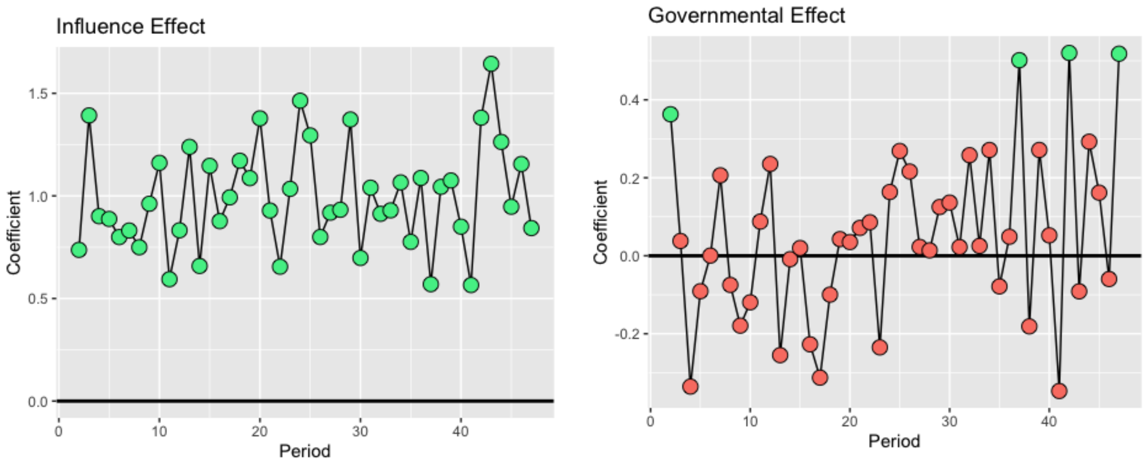

Figure 3. Coefficients for influential and governmental. The green color indicates statistical significance on α = 0.05 level, and red indicates non-significance.

5.2. Popularity effect

Next, I move on to fit model (2), which adds the popularity effect to the baseline model. As with the previous model, the results are plotted by the model term coefficients. This time *p*-values are indicated for the coefficient for each term and for the ANOVA test conducted between the model and its lower degree model on $\alpha = 0.05$ level. This is done to test whether adding the new term increases the model fit and adds to the model's explanatory power. A clarifying scheme on which models include new terms and how the models are tested against each other is presented in table 3.

	Terms included	**Tested against**
Model 1 (m1)	Influence and government effects + additional baseline model terms	-
Model 2 (m2)	all terms in m1 + popularity effect	m1
Model 3 (m3)	all terms in m2 + influence in-degree	m2
Model 4 (m4)	all terms in m2 + government in-degree	m2

Table 3. Description on which terms are included to which models and how the models are tested.

In model (2), I include the baseline model terms and the popularity term. The ANOVA test against the model (1) indicates whether the model fit is improved after adding the popularity in-degree term to the baseline model. The coefficients and p-values for the term in model (2) are plotted in figure 4. The parameter is statistically significant, and the model fit improves in approximately two-thirds of the periods. In the significant periods, the term is also always positive, indicating that there can be distinguished an effect of prior centrality to receiving ties in the present. As the term is non-significant in almost one-third of the modeled networks, the effect is not global during the whole study period. Thus, it cannot be constated that being highly retweeted always predicts even more ties in the Twitter network. The results give local support to the expectation that the popularity effect plays a role in the climate policy Twitter network, as posited by the second research question. This means that popularity is unequally divided in the network, and central actors can influence others to retweet them by their status.

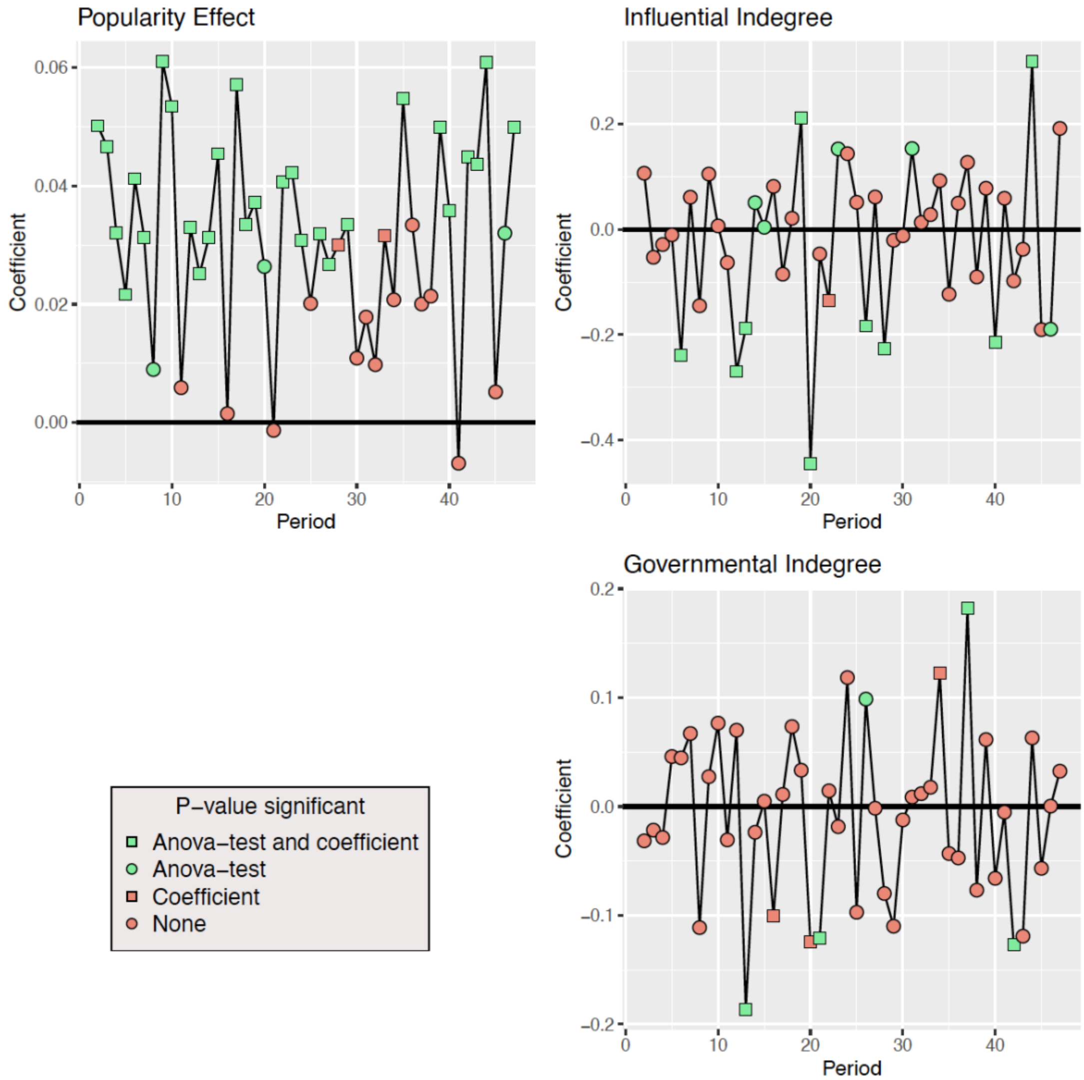

Figure 4. ERGM results for the popularity effect (m2), influence in-degree (m3), and governmental in-degree (m4). The green color indicates a statistically significant ANOVA-test in between the model and the lower degree model, and squares indicate that the *p*-value of the coefficient was significant.

5.3. Influence and government in-degree

The term for influential in-degree is included in the model (3), and the governmental in-degree term is included in the model (4). This time, the terms are added to the model (2) with the popularity term. As the influence and government in-degree terms test the effect of ties from specific actor types during the previous period, the popularity term needs to be included in the models to control for the effect of all kinds of connections. Both higher-level models are then tested against the model (2). The plots presented on the right in figure 4 show that the coefficient varies between positive and negative, and thus, the effect of both in-degree vary between networks. For both parameters, the results are mainly non-significant, indicating that there, for the most part, cannot be found statistically confirmed support for the effect of ties from either type of actor. The results do not support the expectation that being retweeted by influential actors in offline policy networks would yield more retweets. This is the case for influence measured both as formal power and reputational influence. In the context of the policy network communications on Twitter, a powerful actor cannot influence the influence of others. The answer to the third research question, whether ties from influential actors contribute to centrality on Twitter, is negative based on the data used in this study.

5.4. Rest of the model terms

The results for the additional model terms included in the ERGMs are presented in figure 5. The coefficients are plotted for model (2), that provides the most explanatory power of the four models. Figure 5 shows, that the additional model terms included in the analysis help explain the structure of the data. Majority of all homophily coefficients are positive and statistically significant, meaning that organizations are more likely to retweet other organizations of the same type. The past edge and reciprocity effects being overall positive and significant signify that retweets are likely to occur repeatedly between the same actors and that retweeting tends to be reciprocated. The negative edges term points to the fact that the network density in each period is relatively low and receiving ties in the observed networks are less likely than it would be expected in a randomly constructed network. The positive and significant GWESP term denotes that retweets tend to cluster in triangles, as typical in networks. Finally, the GWI degree term coefficient is negative and statistically significant for the majority of the periods (a negative coefficient denotes that the popularity effect exists (Levy, 2016)). As the GWI degree captures similar rich get richer effect as the popularity term, the parameter strengthens the notion that the popularity effect can be found in the Twitter networks.

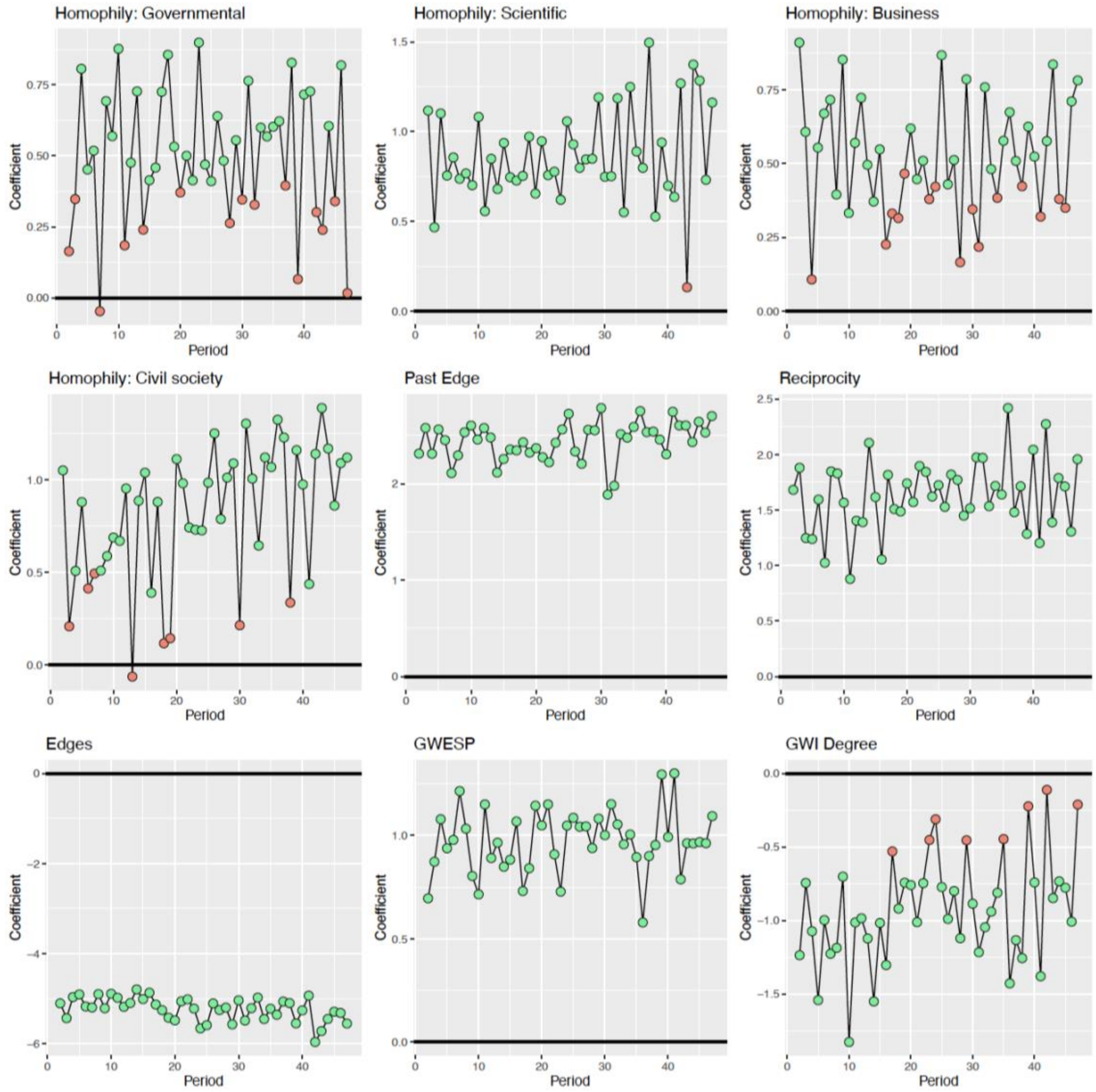

Figure 5. ERGM results for the additional model terms in model 2. GreenThe green color indicates that the coefficient was statistically significant from zero on α = 0.05 level, and red indicates non-significance.

A sample of diagnostics regarding model convergence and fit to data for one randomly chosen period for each model is presented in Appendix C. MCMC diagnostics illustrate the MCMC chains in the simulation process graphically and with summary statistics. The plotting of the simulation shows that the models converged, as the trace of the chains explores the entire parameter space throughout the simulation. The trace being ‘fuzzy’ and not a straight line on the left of the MCMC diagnostics shows that the model is suitable for the data. The goodness-of-fit statistics also illustrate that the models suit the seemingly well to the data. The black line represents the network statistics of the observed network, and the box plots illustrate the simulated networks. (Handcock et al., 2008)

5.5. Robustness test

To test the robustness and strengthen the validity of the results, I ran some additional tests to examine whether the same results could be obtained with retweets that have not been subset by the climate-related keywords and include all retweet activity in between the climate policy network members. With this modification, the number of studied retweets increased from 70 883 to 885 187. Even with this change in the data, the output of model (1) showed that the influence effect was positive and significant in all networks. The impact of being a governmental actor only showed statistical significance in a handful of networks. Including all tweets kept the results regarding the first research question unchanged.

For model (2), there was a slight change compared to the original results, as the number of networks where the popularity effect showed statistically significant results increased. In the networks with all retweets, the popularity term was positive and significant in ¾ of the periods, which means an increase from approximately two-thirds of the coefficients being significant in the initial results. It would be rather unlikely that the popularity effect in tie formation would be significantly different for strictly climate-related discussions than for all interactions in general. It is more probable that the non-significance of the initial results is due to the scarcity of highly retweeted tweets in the data of climate-related retweets. As for the effect of retweets from influential and governmental actors in models (3-4), the results did not show any notable changes as opposed to the climate-related retweets. The test thus indicates more robust support for the finding that influential policy actors' retweets do not generally attract more connections on Twitter.

6. Discussion

6.1. Correspondence in influence online and offline

The research questions stated at the beginning of this thesis were 1) Are influential policy actors central on Twitter? 2) On Twitter, do highly central actors attract even more ties? and 3) On Twitter, do ties from influential policy actors add to an actor's centrality? The results of the fitted ERGMs give varying answers to these questions. The analysis could confirm that actors perceived as highly influential within the policy network receive more retweets than actors on average. I have argued that perceived influence is a fitting measure for actor influence in policy networks and that retweeting functions well as a sign of influence on Twitter. The results support the arguments made by early scholars on the correspondence of online and offline ties by showing that the act of endorsement on Twitter indeed mirrors the relationship in offline policy networks. This study also contradicts results of Cossu et al. (2015) by showing convincingly that offline influence can be spotted in online networks by looking at the interactions within the network, as opposed to merely focusing on the influential actors' own Twitter activity.

Of course, these results do not say much about the direction of the relationship between real-life influence and Twitter centrality. Influence in an offline network might lead to Twitter centrality, or online centrality could contribute to an actor's perceived influence. There can also be a third factor that affects both, such as media coverage, as has been suggested in earlier research on Twitter influence (Chadwick, 2013; Freelon & Karpf, 2015). Despite that, the results allow research on Twitter influence to go one step further and argue that observing retweeting behavior can be used to identify the most influential actors within a network. Thus, Twitter ties can provide a fitting proxy for measuring influence.

I also posited that in addition to influence as reputational power, formal powers would be associated with receiving more ties on Twitter. The empirical results did not support this notion. The finding gives two alternatives for interpretation. It can be seen as a sign of tie formation on Twitter following logic other than that of policy networks, and that several government actors are not that popular on Twitter even though they would be influential and sought-after partners in policymaking offline. Many government agencies are relatively neutral and formal in their Twitter communications, which can lead to their messages not receiving that notable spread. It is also probable that an agency's communications are not that interesting for the greater public to interact with.

This is likely to be the case for many government actors in the data, such as Centres for Economic Development, Transport, and the Environment (ELY Centres). They manage tasks of the central government in issues such as business and industry, transport, and environment, and mainly use Twitter for information about their operations. This would be probable when considering the results of Stier et al. (2018), that found that traditional political elites tend to receive the most central ones on Twitter. Stier et al. (2018) use a different set of actors as the 'traditionally influential ones', focusing only on politicians and media actors already globally influential on Twitter. Thus, it seems likely that some high-profile government actors can attract considerable attention on Twitter, but this notion does not apply to all actors by rule.

The discrepancy between the two types of offline influence could also be partly explained by the fact that perceived influence varies between government entities. Actors such as government agencies are perhaps perceived as less influential in domestic climate policies despite having formal powers. This might have to do with the perception that civil servants are in Finland seen as impartial and thus not perceived to have much to say in outlining policies (Temmes, 2008). However, as shown in policy literature, civil servants within the government and its sub-entities do have considerable power in policymaking in deciding which issues gain attention in government preparation work (Pollitt & Bouckaert, 2017). This power does not translate to a reputation of influence in climate policies, as it can be seen in the top 20 list of most influential actors by the influence survey. This finding supports the premises laid out by Fischer and Sciarini (2015) and Ingold and Leifeld (2016) that having formalized decision-making powers is not the only factor that matters in influencing perceptions in policymaking networks.

Perhaps not surprisingly, the results were similar even when including all retweets between the policy network members in the models. This adds to the robustness of the results and supports the use of different types of Twitter networks in finding the most influential actors. It can also be seen to strengthen the argument that the most influential actors get retweeted due to their influential status, even in issues other than climate policies. It would be likely that influence in one policy issue can spill over even in other policy areas. For example, in the survey used in this study, the respondents were asked which organizations they hold as the most influential ones in domestic climate policies. For a respondent, it can be difficult to discriminate between policy fields when assessing influence capacities. If a respondent is aware of an actor being influential in some other policy area, they might also assess them to be influential in climate policies. Seeing that the Ministry of Environment and other highly climate-related organizations rank at the top of the list of survey-based influence makes the risk of imprecision in influence perception, however, relatively low.

6.2. Popularity affects online influence

The results also support the expectation in the second research question that the popularity effect would affect tie formation in the Twitter policy network. The effect was not robust during the whole study period when only considering tweets with climate-related keywords. These findings align with the ones of Bakshy et al. (2011), that found that previously influential actors tend to be able to attract attention even in the future, but not always. The writers suggested this to be due to the rarity of highly retweeted tweets, which is the most probable explanation for the disappearance of the effect in some periods, even in my study. As the effect was strengthened by the inclusion of the rest of the retweets between the actors, it would thus seem likely, that being highly retweeted attracts even more ties.

This finding sheds light on how influencing works in Twitter networks. Being central, i.e., influential on Twitter, means that an actor can affect their surroundings by attracting more retweets. The fact that both perceived real-life influence and the popularity effect contribute to tie formation implies that centrality on Twitter is not only based on the actor’s characteristics as influential but that this influence also gets built up in network interactions over time. This notion is supported by Golder and Yardi (2010), that found that Twitter users choose to connect with the most central actors, not because they are visible on the platform but simply because their high in-degree makes them desirable contacts. The practical implication of this popularity effect is that an actor that is already perceived as influential has the greater potential to get their messages to travel to larger audiences compared to an actor that is not particularly popular.

This tendency can affect which types of ideas get the most visibility in the network discussions. That the rich get richer principle affects who gets their voice heard within a policymaking arena is not a discovery per se, as actors that are the most visible in policy debates also tend to get the most attention in traditional media platforms. It is, however, a noteworthy finding in the context of a Twitter network, as social media sites are often described as open discussion forums without any hindrance that restricts the access of different voices and interests in the policy discussions. Popularity being unequally distributed amongst the network actors shows that possibilities to participate in discussions vary by how others perceive the actor. The picture of Twitter as a platform where the threshold is low for participation in policy deliberation can be seen to get more varying by these results.

As the monthly networks vary notably in size and the overall density is relatively low, there is a possibility that the lack of statistically significant results is partly due to the scarcity of data. This view is supported by the fact that the results for the popularity effect improved in terms of statistical significance by increasing the number of retweets. The results of retweets from influential actors were unchanged, which could be due to the argument stated above that there are not users popular enough present in the Finnish climate policy Twitter network. Lack of data would seem to be a risk to be aware of when conducting statistical inference on Twitter data. In quantitative Twitter studies, networks are often quite large as the used data sets are collected from the whole of Twitter based on, for example, globally used hashtags. Analyzing actual policy network members that have been handpicked and identified on Twitter leads unavoidably to smaller datasets, as the number of actors, at least in policy systems of smaller countries, is relatively small.

The fact that the popularity effect was not persistent the entire study period, when only climate-related retweets were counted in, could also be seen to imply that the interest in climate issues decreases at times due to policy cycle fluctuations. When climate policy issues are high up on the agenda, more actors participate actively in the policy discussions. During these times, high-profile Twitter users participate in the debate and can gain more retweets by their popularity status. Even actors that generally would not be as popular can utilize the window of opportunity and get more retweets to their messages. As argued by Kingdon (2011), interest groups' influence in policy is highly affected by these periods when the rest of the policy network is also highly concerned with dealing with the problem they work with. In periods when climate issues are not on the daily discussion agenda, actors that during the previous period could attract ties can lose their status, which could result in the disappearance of the popularity effect in the data.

6.3. No effect of influential contacts

Contrary to expectations set in the third research question, being retweeted by influential policy actors did not help actors attract more ties. This was the case for retweets from structurally powerful influencers and formally powerful government actors. Powerful contacts were expected to have an effect on an actor's influence due to how influencing has been seen to function in policy networks. According to Ingold and Leifeld (2016), being connected to powerful partners gives an actor a structurally advantageous position and increases the actor's perceived influence by the mere established contact. As for interest groups communicating their views to decision-makers with formal powers is the only way of having an impact on policy, connections to influential actors could signal that the group is getting their ideas through to policy.

These results can be contrasted with those of earlier research on Twitter influencers in computer sciences, where retweets from highly influential actors have been found to contribute to an actor receiving more retweets (Bakshy et al., 2011; Cha et al., 2010). In these studies, the data consists of interactions between large sets of Twitter users, not only between users representing a specific, limited group of local policy actors. In the cases where influential actors' retweets have been seen to attract even more interactions with the originator of the message, the influential accounts have belonged to globally famous individuals on Twitter, such as celebrities, social media influencers, and other opinion leaders. A similar result has been found by Garcia et al. (2017), that concludes that being connected to powerful partners contributes to an actor's retweet rates only in cases where the retweeting account is a significantly central actor in the overall Twitter system.

In the Finnish climate policy network context, no single actor seems to have the power needed to draw attention to another actor by their endorsements. This discovery suggests that retweeting, although a visible indicator of established contact, does not contain a signaling effect where the influence of the ego would increase alter's influence. The research design with monthly networks might also have contributed to the lack of effect. As the retweets from influential actors are counted from the whole previous month before the modeled network, it is not entirely unthinkable that the impact of a retweet at the beginning of period *t*-1 would have faded at the end of period *t*, almost two months later. However, it is more likely that the behavior patterns found in offline policy networks and large online networks of several millions of Twitter users do not apply to small subsets of Twitter interaction.

This finding supports the idea that even though the two types of measuring influence seem to correlate, scholars should still apply cautiousness when considering two types of ties as equal. Berardo et al. (2020) argued that dichotomizing diverging ties could lead to misleading interpretations of the network structure, as different types of connections can generate different relation patterns. This study has shown that influencing in Twitter networks does not follow the same patterns as expected in offline networks. This calls for more multidisciplined research to determine how different types of offline partnerships could be seen to be manifested in social media interactions.

6.4. Implications for Finnish climate policy network

Examining the list of most influential actors as measured in the offline survey shows that a country can decide on ambitious climate policies despite business and industry representatives being highly influential within the policy field. This could indicate that even though an actor would be perceived as influential, it does not necessarily mean that they have had a notable effect on policy (Dahl, 1957). It has although been estimated that the government's mitigation measures this far are not enough for Finland to reach the carbon neutrality target by 2035. The privileged status of pro-economy actors would seem to continue to play a role in policy implementation. However, it is noteworthy that the ambitious targets were set in the first place, despite the strong status of the business and industry organizations. This could support the notion that a government constellation with green-leftist parties could be beneficial for pro-mitigation policies to take place.

The result that the most influential policy actors could be identified with Twitter data shows that Twitter is broadly used by influential policy actors to advocate for their policy views. However, in the descriptive analysis, differences in which actors are most influential offline and the most central online could be seen. The top of the offline influence list consists mainly of pro-economy organizations, but the most retweeted actors are largely pro-climate government actors, civil society organizations, and research institutes. This could indicate that whereas pro-economy actors are privileged in offline policy processes, the pro-climate side would dominate in the Twitter discourse. Knowing that the popularity effect plays in which actors are most central on Twitter, the discussion arena on Twitter seems advantageous for the pro-climate side in getting their voice heard.

A central position on Twitter could thus be seen to be a result of popularity being based on an actor's reputation as a strong pro-climate advocate. Ingold and Fischer (2014) have found that collaboration in climate change mitigation was explained to a wider extent by shared policy beliefs than power. This could be seen to apply to Twitter connections, as in addition to endorsements, retweeting is also seen to signal an agreement and partisan alignment (Conover et al., 2011). The notion that actors tweet organizations with similar views is supported by looking at the additional model effects included in the ERGM. The fact that the homophily effect affects the likelihood of receiving ties strengthens the view that the most retweeted actors have obtained their position due to one side triumphing the other in the overall discourse.

The dominance of the pro-climate side in Twitter discussions can be seen to be bolstered by the broad mobilization of the environmental movement on Twitter (Thompson, 2020). This visibility of environmental civil society actors on Twitter has been utilized by political parties that have sought to associate themselves with the popular citizen movement (Savolainen & Ylä-Anttila, 2021). To the difficulty of the pro-economy side getting their views through adds, that it is morally difficult to publicly be 'against' stopping climate change (Lazarus, 2008). Earlier research has concluded that the vast majority of actors within the Finnish climate policy arena believe in anthropogenic climate change (Wagner et al., 2021) and that the Finnish Twittersphere is not particularly divided in climate policy issues (Chen et al., 2021b). The non-existence of radically diverging views in the policy discourse is also supported by the data in this study, as the only organized interest group that is openly skeptical of climate change, the civil society organization Ilmastofoorumi (‘Climate Forum’), has only a total of four retweets.

The finding that the actors with formal, institutionalized powers do not appear particularly central on social media can affect the greater public’s views on who is to praise or blame for policy decisions made. According to the Finnish climate barometer in 2019, the vast majority of Finnish citizens are in favor of the government deciding on effective climate mitigation measures[12]. That the climate policies do not reflect this view raises the question of whether the public authorities make decisions based on the will of the people or a privileged interest group within the policy system. The network perspective on governance has been criticized due to how the issue of accountability can become obscured in the policy processes (Urbinati & Warren, 2008). Thus, powerful opinion leaders outside of the formal decision-making processes being largely visible but not influential in policy can shift the focus from who actually is responsible for the decisions made.

A broadly pro-climate Twittersphere would seem to be fitting for a country with ambitious goals to reach carbon neutrality. However, the dominance of the established pro-climate actors can constrain new or alternative views from accessing the policy arena on the public discussion forums in social media. As climate policies are intrinsically social issues and can create economic winners and losers based on the decision-makers' values, beliefs and interests, a broad range of different views need to be accounted for in the policy process. The fact that scientific research institutes and universities are central to climate communications is good news for the overall policymaking environment. This implies that the scientifically proven information has a strong position in the Finnish climate policy debate, even though the government’s measures are still lagging the stated targets. Future research will be needed to confirm whether this pro-climate discourse in policy discussions can break the influence of pro-economy actors in actual policy negotiations.

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[12] Ilmastobarometri, 2019

7. Conclusions

The main reason to study influence in public policy is the importance of knowing, who interacts with whom, and how it affects the decisions made. This task has become easier with the emergence of social media platforms where relations between policy actors can be observed openly. In this thesis, I have shown that influence in policy networks can be studied with social media connections. The fact that influence is exerted by the same actors offline and online strengthens the argument that social media poses a fruitful platform to examine in policy studies. However, as ties from real-life policy influencers did not bolster actors' online influence, the results show that not all types of social dynamics common in policy networks can be studied online. These findings should encourage researchers in multiple fields to continue exploring how online data sources can be used and which types of information they can provide about interactions within real-life policy networks.

The analysis adds to the literature also by demonstrating that in online networks, influence gets constructed through interaction, and the 'rich get richer' principle affects who gets their voice heard in the policy discussions. The empirical case of climate change policymaking in Finland illustrates that this can have implications in forming of the policy discourse online. As the most retweeted actors were significant advocates on the pro-climate side, the Twitter discourse amongst important policymakers would be expected to be dominantly pro-climate. This does not necessarily mean that the critical actors in formal policy processes would be as committed to ambitious policy targets as the general discourse would imply. Pro-economy government and business actors that are not particularly visible online, but have a notable effect in offline bargaining processes, can alter this view to a great extent when the actual decisions are made. Thus, influence accumulating to a certain type of actors can give a misleading impression of the plurality of interests accounted for in the policy outcomes.

The results of this study should be interpreted with consideration to the limitations posed by the chosen research design. Firstly, a group of actors with notable influence in policy processes, media organizations, were left out of the analysis. Even though mainstream media in Finland is mainly non-partisan, leaving them out means omitting the role of actors that contribute largely to shaping the context and public discussion on policy problems. Secondly, the research design should only be seen as applicable to contexts where Twitter is actively used in policy debates. In countries where Twitter is not that commonly used or where it is used only by specific type of actor groups, studying Twitter could give a highly biased image of the power dynamics of the policy debates. Lastly, the results can be impacted by the technical choices made during the data processing of Twitter data. In future iterations of similar study designs, researchers should thus consider using even more advanced computational technics to narrow down the tweet corpus for climate-related discussions on social media.

In future research, scholars should look at differences in climate beliefs as determinators for tie formation online. In this thesis, I divided actors into ‘pro-economy’ and ‘pro-climate’ actors. This division entails a rather crude simplification of the various views and opinions regarding climate policy measures. Content analysis on discourses within the climate discussion could paint a more diverged picture of the different arguments used in the debates. Future endeavors should also consider continuing to examine ‘strong’ and ‘weak’ ties on Twitter after the typology of Granovetter (1973). In this thesis, a single retweet between two accounts of any of the three account types formed a tie between the two organizations. Connections could also be valued based on which type of actor sends it or whether the actors exchange retweets several times under a certain period. Lastly, similar approaches examining several different types of ties between the same policy actors could benefit from the recent developments within multiplex network analysis (Chen, 2021). Modeling the different kinds of ties simultaneously could provide insight into the interdependency and possible mutual reinforcement between offline and online relations.

This thesis is conducted in the context of Twitter networks, but it should be kept in mind that the social media field is still constantly changing; a site the most broadly used for policy debates today might not be that tomorrow. Although vital for societal discussions, Twitter and other social media sites serve the needs of for-profit corporations. That being the case, changes to inherent operation principles can alter the prerequisites and functionality of Twitter as a platform for meaningful policy debates. Even though one individual social media site would become less attractive to interact within, the short history of social media sites has shown that there would be another one to fill the void. It can be argued, that the benefits of social media as a direct, low-threshold communication channel have moved policy debates online for good.

Seeing that centrality on Twitter is telling of real-life influence, public policy scholars can take the next step to argue that social media not only mirrors ‘real-life’ behavior but is also a vital part of it. Social media is one of the main ways for people to connect, socialize with like-minded, and engage in politics and social movements, which makes it an inherent part of social and political life in contemporary societies. The discussion should thus progress from ‘do social media ties matter’ to addressing how all the different platforms for policymaking, traditional media, social media, and citizen activism, together can affect policy processes and which types of synergies they generate for actors’ influence.

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Appendix A

The R code used for the data processing and the ERGM analysis.

```
library(gridExtra)
library(statnet)
library(dplyr)
library(devtools)
library(lubridate)
library(Rglpk)
library(ggplot2)
###
## ---------------- Upload the data --------------- ##
###
# Edgelist
edgelist <- read.csv('~/Documents/edgelist.csv', sep =',',
                   colClasses = c('id'='character', 'author_id'='character',
                                  'ref_id'='character', 'ref_author_id'='character'),
                     encoding = 'UTF-8')
# Node attributes Twitter
all_accounts <- read.csv("~/Documents/all_accounts.csv", colClasses = c('id'='character'), sep =',')
# Node attributes survey
df.full <- read.csv2("~/Documents/COMPON_FI_R2_attributes.csv")
# Survey networks
n1 <- read.csv2("~/Documents/COMPON_FI_R2_N1L.csv")
# List of keywords
keywords <- read.csv('~/Documents/climateKeysAP.csv', sep =',', header = F, stringsAsFactors = F)

###
## --------------- Cleaning the data ------------ ##
###
# Subset twitter data to retweets during 2018 - 2021
nt.retweet <- subset(edgelist, edgelist$type=="retweeted",
                     select=c(author_id, ref_author_id, text, ref_text, created_at))
ymd_hms(nt.retweet$created_at, tz = "UTC")
nt.18_21 <- subset(nt.retweet, nt.retweet$created_at >= "2018-01-01 00:00:00"
                   & nt.retweet$created_at < "2022-01-01 00:00:00")
# Remove FX-accounts
accounts <- all_accounts[-which(startsWith(all_accounts$org, "FX")),]
## Change the label of all polparties to 15
df.full[df.full$OT_SUB==16, "OT_SUB"] <- 15
### Exclude non-responding orgs
df <- subset(df.full, df.full$statusR2<3,
             select=c(ID, id_orig, org_R2, country, statusR2, OT_BIG, OT_SUB))

##### -------------------- Influence network ------------------ ###
# Remove actors with status > 2
n1 <- subset(n1, (!Alter %in% c("FI097", "FI098", "FI099", "FI100", "FI101", "FI102", "FI103","FI104",
                                "FI105", "FI106", "FI107", "FI108", "FI109", "FI110", "FI111"
                               ,"FI112", "FI113", "FI114", "FI115", "FI116", "FI117","FI118" ,
                                "FI119" ,"FI120", "FI121", "FI122" ,"FI123", "FI124")))
n1 <- n1[-which(n1$ID==n1$Alter),]
# apply the summation per value -> count influence in-degree
actorlist <- df$ID
inf_indeg <- data.frame(sapply(n1,
                        function(n1) table(factor(n1, levels = actorlist))))
inf_indeg <- inf_indeg$Alter
inf_factor <- scales::rescale(inf_indeg)
df$n1 <- NA
df$n1 <- inf_factor
df$n1_factor <- NA
df$n1_factor <- inf_indeg

# Merge the edgelist and all_accounts by sender & receiver ID
attr.0 <- merge(nt.18_21, accounts, by.x = "author_id", by.y = "id", all.x = FALSE,
                     all.y = FALSE)
nt.attr.0 <- merge(attr.0, accounts, by.x="ref_author_id", by.y="id",
                   all.x = FALSE, all.y = FALSE, suffixes = c("_sender", "_receiver"))
nt.attr.0 <- select(nt.attr.0, text, ref_text, created_at, ends_with("sender"), ends_with("receiver"))

# Include organization type
attr.0.receiver <- merge(nt.attr.0, df, by.x = "org_receiver", by.y="ID", all.x= F, all.y=F)
nt.attr <- merge(attr.0.receiver, df, by.x="org_sender", by.y="ID", all.x=F, all.y=F,
                 suffixes = c("_receiver", "_sender"))
```

```r
nt.attr <- select(nt.attr, org_sender, org_receiver, text, ref_text,
                  sn_sender, sn_receiver, org_R2_sender, org_R2_receiver, level_sender, level_receiver,
                  OT_SUB_sender, OT_SUB_receiver, OT_BIG_sender, OT_BIG_receiver,n1_sender,n1_receiver,
                  created_at)
nt <- nt.attr
rm(attr.0, attr.0.receiver, nt.attr.0)

### Subset edgelist nt to climate keywords
keywords150 <- keywords[c(1:150),]
keywords_rest <- keywords[c(151:332),]
# To strings
keywords150 <- paste0(keywords150, collapse="|")
keywords_rest <- paste0(keywords_rest, collapse="|")
# Grepl() tweets with keywords
keywords_firstpart <- nt[which(grepl(keywords150, nt$ref_text)),]
keywords_secondpart<- nt[which(grepl(keywords_rest, nt$ref_text)),]
# Combine the two sets
nt.climate <- rbind(keywords_firstpart, keywords_secondpart)
# Remove duplicates
nt.climate <- nt.climate[-which(duplicated(nt.climate)),]
# Remove self-ties
nt.climate <- nt.climate[-which(nt.climate$sn_sender==nt.climate$sn_receiver),]

####
### -------------- Subset by levels ------------ ###
####
nt.climate_0_1_2 <- subset(nt.climate, nt.climate$level_sender<3 & nt.climate$level_receiver<3)
####
### ------------- Change level of MPs and MEPs to 1 ----------- ###
#####
# Subset to ties where one part is a political party
nt.polpart <- subset(nt.climate, nt.climate$OT_SUB_sender==15 |
                       nt.climate$OT_SUB_receiver==15)
# Subset to edges where one node is MP or MEP
nt.mp <- subset(nt.polpart, (nt.polpart$level_sender==3 & nt.polpart$OT_SUB_sender==15)
                | (nt.polpart$level_receiver==3 & nt.polpart$OT_SUB_receiver==15))
# Change ALL LEVELS of political parties to 1
nt.mp[(nt.mp$OT_SUB_sender==15 & nt.mp$level_sender==3), "level_sender"] <- 1
nt.mp[(nt.mp$OT_SUB_receiver==15 & nt.mp$level_receiver==3), "level_receiver"] <- 1
# Delete edges where actor level is 3
nt.mp <- subset(nt.mp, nt.mp$level_sender<3 & nt.mp$level_receiver<3)
# Add the MP and MEP ties to data frames with levels 0 1 and 0, 1, 2
nt.climate <- rbind(nt.climate_0_1_2, nt.mp)
rm(nt.mp, nt.polpart)
##
### ----------Add weeks and windows to the edgelist ----------- ###
##
addWeeksWindows <- function(edgelist){
  # cleaning dates
  edgelist$created_at <- parse_date_time(edgelist$created_at, 'ymd HMS', tz = 'UTC')
  # sort data by created_at
  edgelist<- edgelist[order(as.Date(edgelist$created_at, format="%d/%m/%Y %H%M%S")),]
  # convert timestamp to weeks running from Sat to Fri, starting with 1
  edgelist$week <- isoweek(edgelist$created_at + days(2))    # to Sat-Fri week
  newyear <- which(diff(edgelist$week) < 0) + 1             # count weeks in new year starting with pri
or year's week counter
  for(ind in rev(newyear)){                                 # adding prior year's week number to new ye
ar's
    edgelist$week[ind:nrow(edgelist)] <- edgelist$week[ind:nrow(edgelist)] + edgelist$week[ind - 1]
  }
  edgelist$week <- edgelist$week - min(edgelist$week) + 1

  edgelist$window <- month(edgelist$created_at)
  newyear_window <- which(diff(edgelist$window) < 0) + 1
  for(ind in rev(newyear_window)) edgelist$window[ind:nrow(edgelist)] <- edgelist$window[ind:nrow(edgel
ist)] + edgelist$window[ind - 1]
  }
  edgelist
}
nt.climate <- addWeeksWindows(nt.climate)
```

```
################################################
##### ---------- Make networks ----------- #####
################################################
###
## --------- Create matrices-------- ##
###
createMatrix <- function(edgelist, window_number){
  # Subset to periods
  edgelist <- subset(edgelist, edgelist$window==window_number)
  # Remove duplicates
  edgelist <- edgelist[-which(duplicated(edgelist[,c('org_sender', 'org_receiver')])),c('org_sender', '
org_receiver')]
  # Create an empty matrix
  mat <- matrix(0, nrow = 104, ncol = 104)
  # Giving the matrices col and row names
  colnames(mat) <- rownames(mat) <- df[1:104,1]
  # Fill in the matrix cell if there exists an edge between the row-col actors in the edgelist data
  for(i in 1:nrow(edgelist)){
    if(edgelist[i,1] %in% colnames(mat) & edgelist[i,2] %in% colnames(mat)){
      mat[edgelist[i,1],edgelist[i,2]] <- 1
    }
  }
  # Remove loops
  diag(mat) <- 0
  mat
}

# Loop to create matrices of all 48 windows
matlist <- list()
for(window_i in 1:48){
  matlist[[window_i]] <- createMatrix(nt.climate, window_number  = window_i)
}
matlist
###
## --------- Create networks and assign node attributes --------- ##
###
createNetwork <- function(mat, mat_t_1){
  # Make network object
  nw <- network(mat, directed = T)
  # Assign vertex subtypes
  nw%v%"OT_BIG" <- df$OT_BIG
  nw%v%'allciv' <- ifelse(nw%v%'OT_BIG' %in% 4, 1, 0) # specifying civil society
  nw%v%'pol' <- ifelse(nw%v%'OT_BIG' %in% 1, 1, 0) # specifying governmental actors
  nw%v%'sci' <- ifelse(nw%v%'OT_BIG' %in% 2, 1, 0) # specifying scientific organizations
  nw%v%'business' <- ifelse(nw%v%'OT_BIG' %in% 3, 1, 0) # specifying business actors

  # Assign matrix t-1
  mat_window <- mat_t_1
  # Alldeg
  nw%v%'all_deg' <- colSums(mat_window)
  # Poldeg
  nw%v%'pol_deg' <- colSums(mat_window[as.logical(nw%v%'pol'),])
  # Influence
  nw%v%'inf' <- df$n1
  nw%v%'inf_deg'  <- colSums(mat_window * nw%v%'inf')
  nw
}

# Loop to create 47 networks with node attributes (periods 2-48)
nwlist <- list()
for(mat_i in 2:48){
  nwlist[[(mat_i-1)]] <- createNetwork(mat = matlist[[mat_i]],
                                       mat_t_1 = matlist[[(mat_i-1)]])
}
nwlist
names(nwlist) <- c(2:48)
# Add the first period back in
matlist.1 <- matlist[[1]]
nw.1 <- network(matlist.1, directed = T)
nw.1 <- list(nw.1)
nwlist <- c(nw.1, nwlist)
names(nwlist) <- c(1:48)
rm(matlist.1, nw.1)
```

```r
## ---------------- ERGMs ---------------- ##
# M1
m1 <- list()
for(nw_i in 2:48){
  nw <- nwlist[[nw_i]]
  nw_past <- nwlist[[nw_i-1]]
  m <- ergm(nw ~ edges
            + nodeicov('inf')
            + nodeicov('pol')
            + nodematch('OT_BIG', diff=T)
            + edgecov(nw_past)
            + mutual
            + gwesp(decay=0, fixed=T)
            + gwidegree(decay=0, fixed=T)
            ,control = control.ergm(seed = 160222))
  m1[[(nw_i)]] <- m}
m1 <- m1[c(2:48)]
# M2
m2 <- list()
for(nw_i in 2:48){
  nw <- nwlist[[nw_i]]
  nw_past <- nwlist[[nw_i-1]]
  m <- ergm(nw ~ edges
            + nodeicov('inf')
            + nodeicov('pol')
            + nodematch('OT_BIG', diff=T)
            + edgecov(nw_past)
            + mutual
            + gwesp(decay=0, fixed=T)
            + gwidegree(decay=0, fixed=T)
            + nodeicov('all_deg')
            ,control = control.ergm(seed = 160222))
  m2[[(nw_i)]] <- m
}
m2 <- m2[c(2:48)]
# M3 with infdeg
m3 <- list()
for(nw_i in 2:48){
  nw <- nwlist[[nw_i]]
  nw_past <- nwlist[[nw_i-1]]
  m <- ergm(nw ~ edges
            + nodeicov('inf')
            + nodeicov('pol')
            + nodematch('OT_BIG', diff=T)
            + edgecov(nw_past)
            + mutual
            + gwesp(decay=0, fixed=T)
            + gwidegree(decay=0, fixed=T)
            + nodeicov('all_deg')
            + nodeicov('inf_deg')
            ,control = control.ergm(seed = 160222))
  m3[[(nw_i)]] <- m
}
m3 <- m3[c(2:48)]
# M4 pol in-degree
m4 <- list()
for(nw_i in 2:48){
  nw <- nwlist[[nw_i]]
  nw_past <- nwlist[[nw_i-1]]
  m <- ergm(nw ~ edges
            + nodeicov('inf')
            + nodeicov('pol')
            + nodematch('OT_BIG', diff=T)
            + edgecov(nw_past)
            + mutual
            + gwesp(decay=0, fixed=T)
            + gwidegree(decay=0, fixed=T)
            + nodeicov('all_deg')
            + nodeicov('pol_deg')
            ,control = control.ergm(seed = 160222))
  m4[[(nw_i)]] <- m
}
m4 <- m4[c(2:48)]
```

Appendix B

The keywords for subsetting climate-related retweets

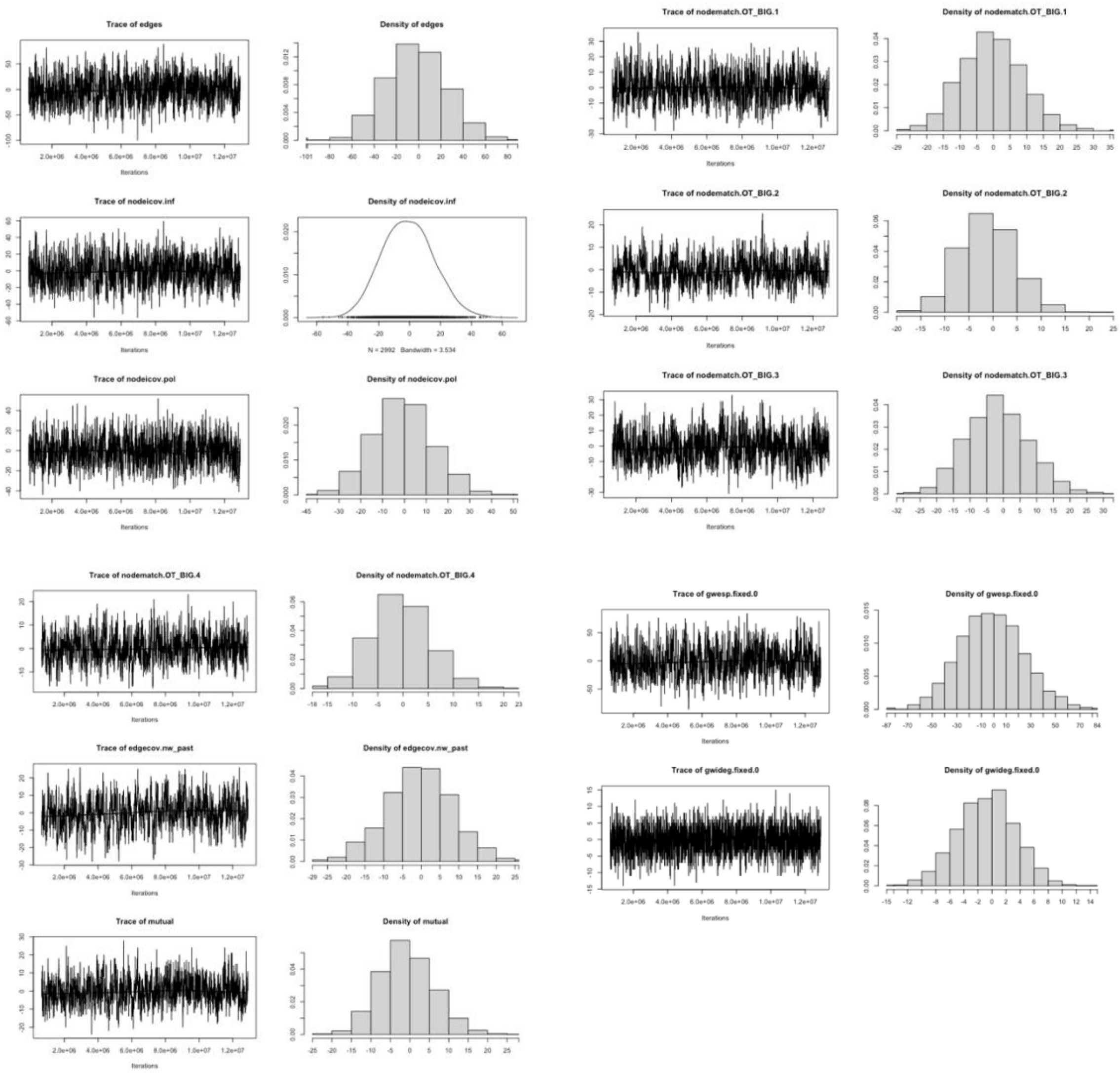
climate	kestävä kehit	puhdasta tekni	ydinvoima
global warming	kestävän kehit	puhtaan tekno	atomivoima
globalwarming	hållbarhet	puhtaan tekni	ydinjäte
ilmasto	hållbar utveckl	ren tekno	reaktori
klimat	energy	ren tekni	kärnkraft
environment	energia	capture and storage	kärnavfall
ympäristö	energi	capture & storage	reaktor
miljö	electric	talteenot	indigenous people
ecolog	sähkö	kolfångst	indigenous communit
ekologi	elektrisk	renewable	alkuperäiskans
ekolog	fossil	uusiutuva	alkuperäisväest
nature	fossiili	förnybar	ursprungsbefolk
luonnon	fossila	intermittency	scrapping premium
uhanalai	coal	säätövoima	romutuspalkkio
luonto	carbon	lauhdevoima	skrotningspremie
biodiversity	hiili	intermittens	flying
biodiversiteetti	hiile	justeringskraft	aviation
biologisk mångfald	koldioxid	solar power	airplane
natur	natural gas	aurinkovoima	aeroplane
sukupuuttoaal	biogas	aurinkoa	lentä
massasukupuut	bio gas	solkraft	lento
extinction	maakaasu	wind power	ilmailu
utrotning	biokaasu	tuulivoima	flyg
massutdöende	kaasuauto	tuulta	forest
emission	natur gas	vindkraft	metsä
päästö	gasbil	turbine	skog
utsläpp	fuel	turbiini	agricultur
methane	combustion	turbin	maatalou
metaani	polttoaine	geotherm	lantbruk
metan	polttomoottor	geotermin	jordbruk
greenhouse gas	bränsl	geotermis	nielu
greenhousegas	förbränn	non-ets	sänka
kasvihuoneilmiö	kerosene	non ets	sänkor
greenhouse effect	kerosiini	taakanja	harvest
kasvihuonekaas	kerosin	bördefördelning	logging
växthuseffekt	cleantech	heat pump	clearfell
växthusgas	clean tech	lämpöpump	clearcut
sustainability	puhdas tekno	värmepump	hakku
sustainable develop	puhdas tekni	nuclear	puuviljelmä
kestävyy	puhdasta tekno	reactor	avverkn

kalhygg
wood constructi
wooden constructi
wooden element
wooden frame
wooden building
wooden multi
puuraken
puutalo
puuelement
puukerrostalo
träkonstrukti
träbyggn
träelement
trävåningshus
concrete constructi
concrete element
concrete frame
concrete building
betoniraken
betonitalo
betonielement
betonikerrostalo
betongkonstrukti
betongbyggn
betongelement
betongvåningshus
fertiliz
fertilis
lannoit
befrukt
continuous cover
jatkuvapeittei
jatkuva kasvatu
jatkuvan kasvatu
kontinuerligt täck
sámi
sáme
sami people
saamelai
samerna
samiska
peat
turve
turpee
hydro power
vesivoima
vattenkraft
hydrogen
vety
fotogen
congestion
ruuhkamaksu
trängselskatt
trängselavgift
car fleet
autokanta
autokannan
bilflotta
decoupl
irtikytk
frikoppl
cycling
pyöräil
cykling
jatkuva kasvu
jatkuvan kasvu
ekonomisk tillväxt
kontinuerligt tillväxt
Infinite growth
bioeconom
green econom
circular econom
green growth
greengrowth
sustainable growth
sustainablegrowth
biotalou
vihreä talou
kiertotalou
vihreä kasvu
vihreäkasvu
kestävä kasvu
kestävän kasvu
kestäväkasvu
bioekonom
grön ekonom
cirkulär ekonom
grön tillväxt
gröntillväxt
hållbar tillväxt
hållbartillväxt
innovativ
innovation
innovatiiv
innovaatio
harmful subsid
haitalliset tuet
haitalliset tuki
haitallisten tuki
skadliga subvention
settlement struct
nytonpakko
nyt on pakko
extinction rebellion
elokapina
greta
thunberg
taalas
taalaksen
datteln
uniper
cap-and-trade
cap and trade
capandtrade
cap-n-trade
cap n trade
capntrade
power-to-x
power to x
powertox
onkalo
afolu
lulucf
redd
beccs
ipcc
ipbes
cop1
cop2
15 aste
puolentoista aste
1.5 degree
1.5-degree
elinkelpoinen
elinkelpoisen
taxonomi
taxonomy
taksonomia
fit for 55
fitfor55
green deal
greendeal
greenpeace
viherpesu
green washing
fillarikommunis
FFFSuomi
fridays for future
koululakko
koululako
school strike
skolstrejk
#korvaamaton
naudanliha
lihatalou
maitotalou
kukkakaalipirtelö
kasvisruo
vegaani
meat industry
dairy industry
milk production
köttindustri
mjölkindustri
vegan
nötkött
beef
plantbased
plant-based
plant based
växtbasera

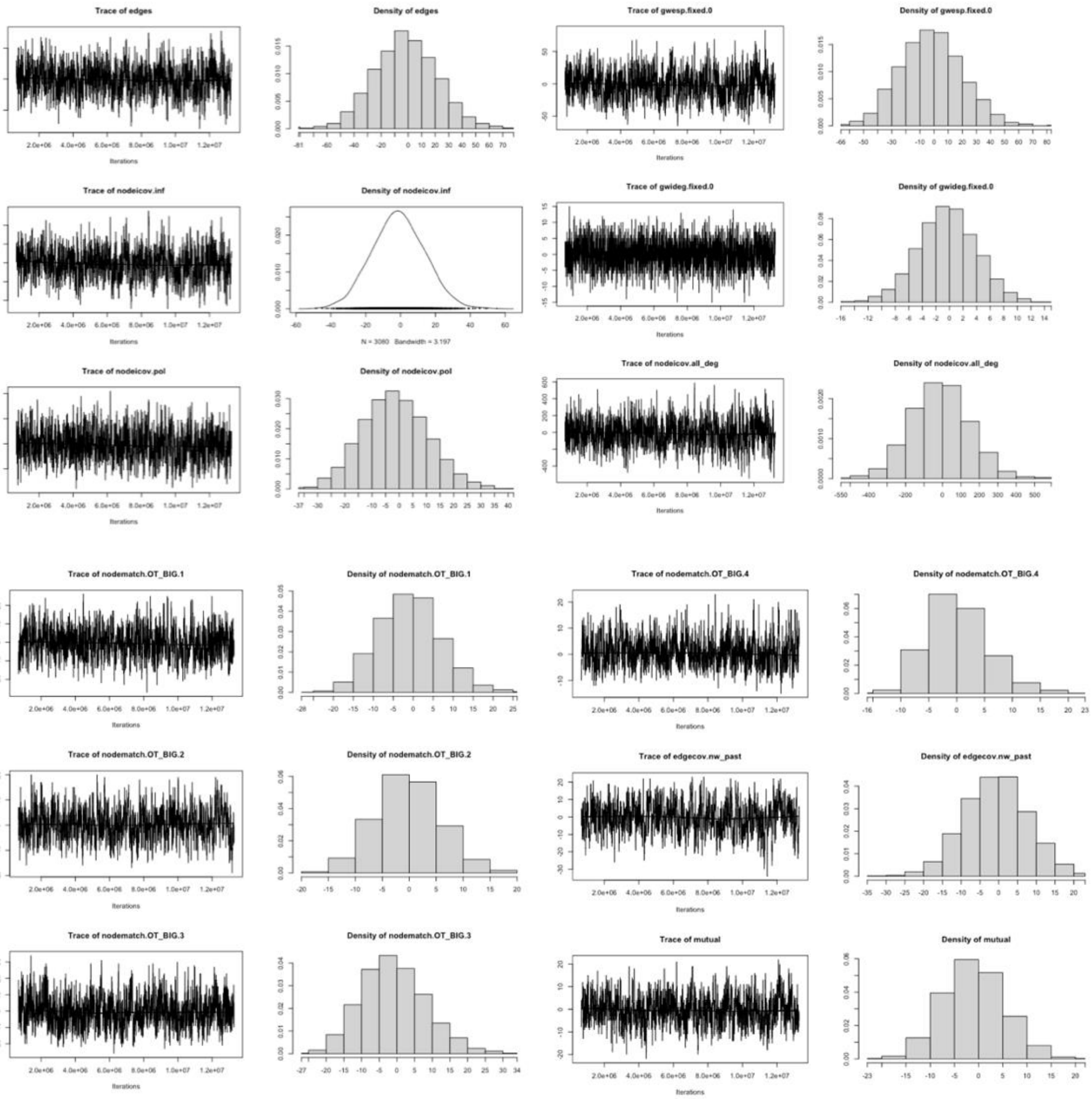
Appendix C

Goodness-of-fit and MCMC-diagnostics plots for one randomly chosen network in each of the four ERGMs.

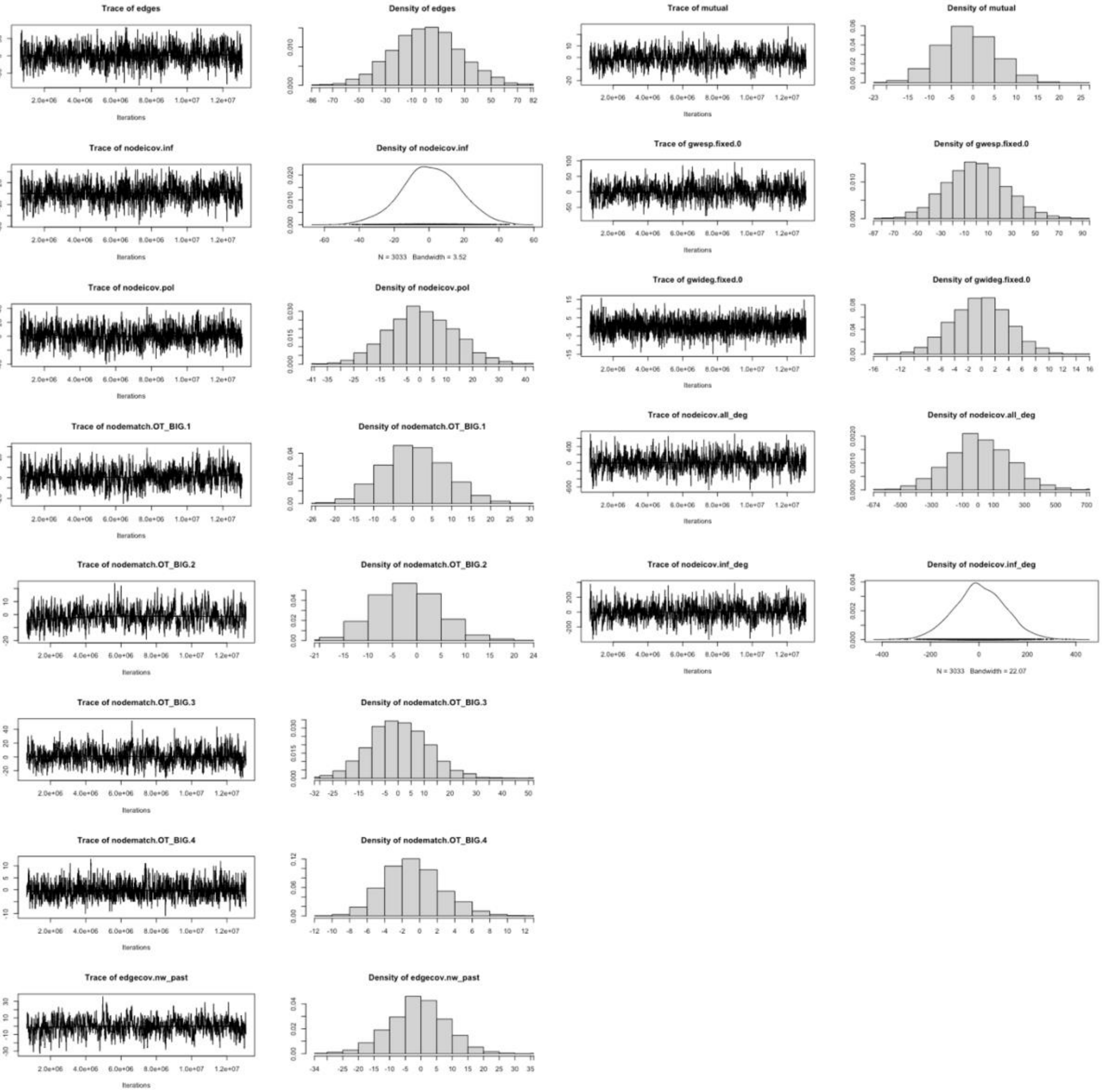
MCMC-diagnostics for Model 1, Period 32



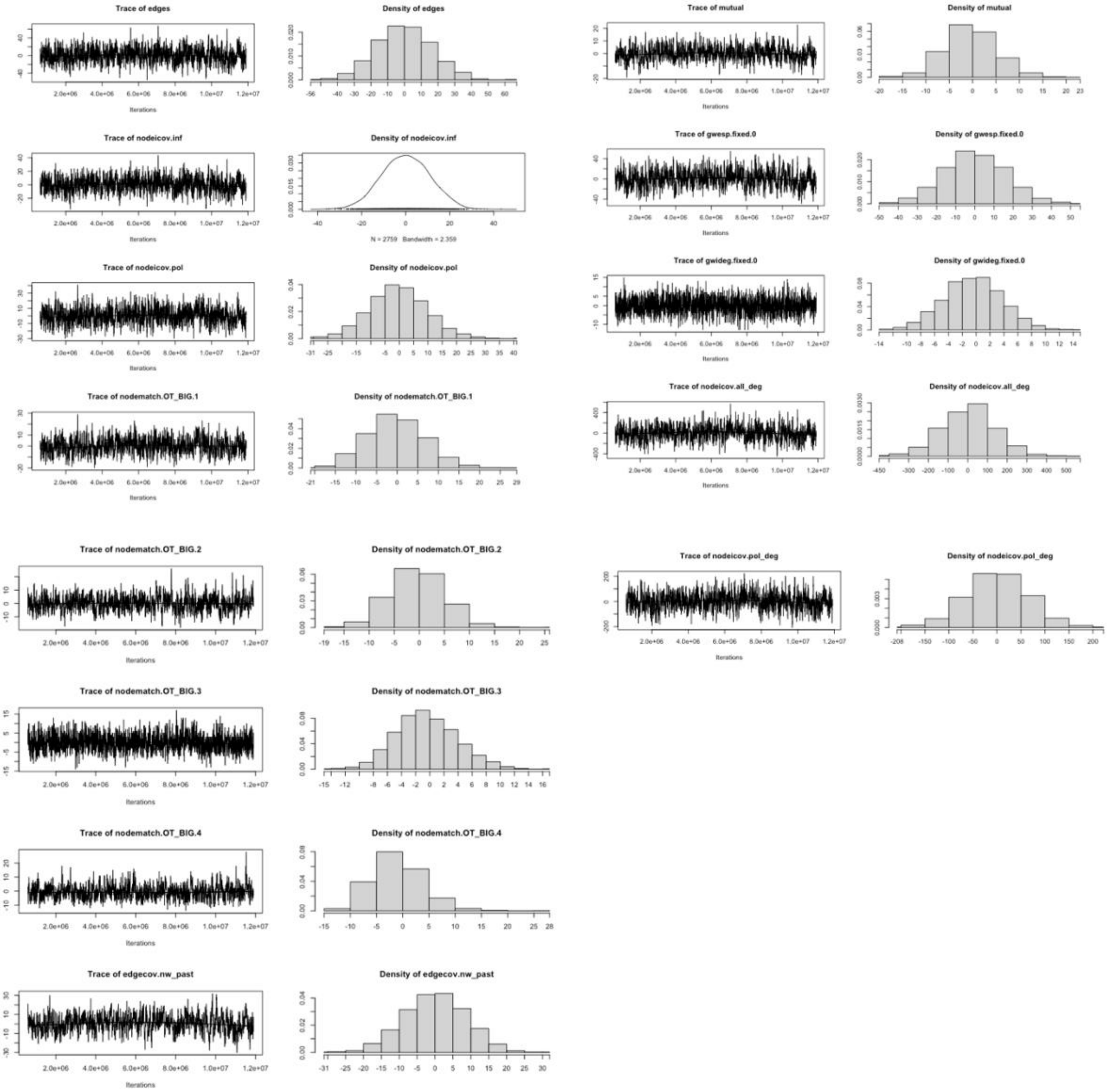
Model 2, Period 24



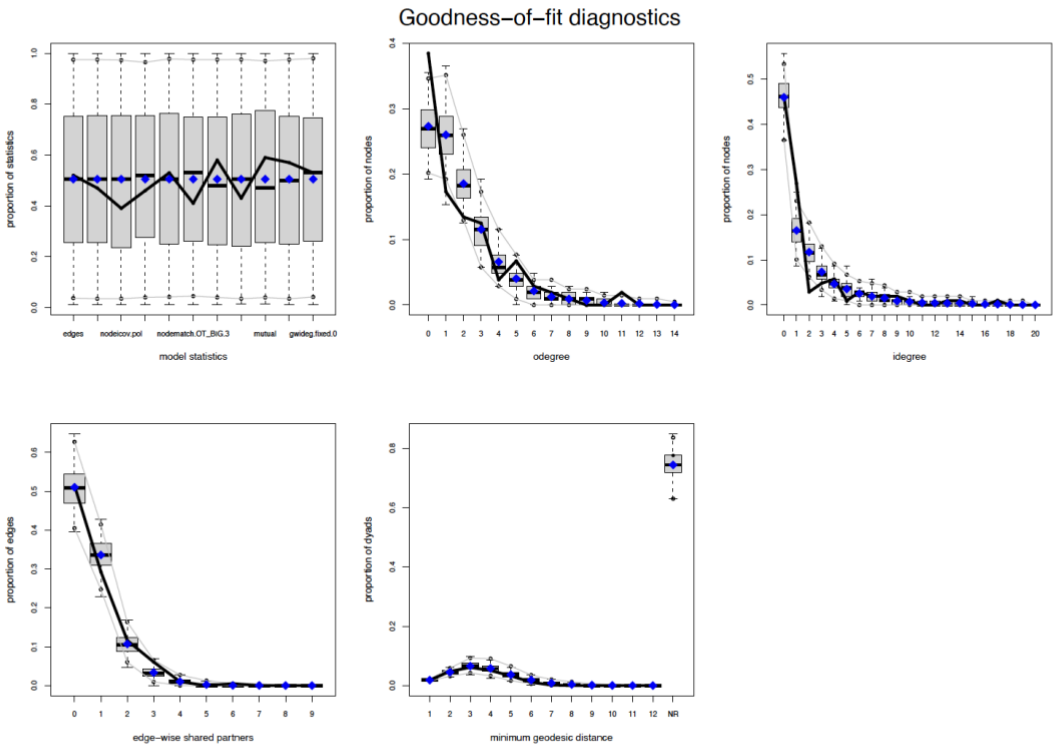
Model 3, Period 12



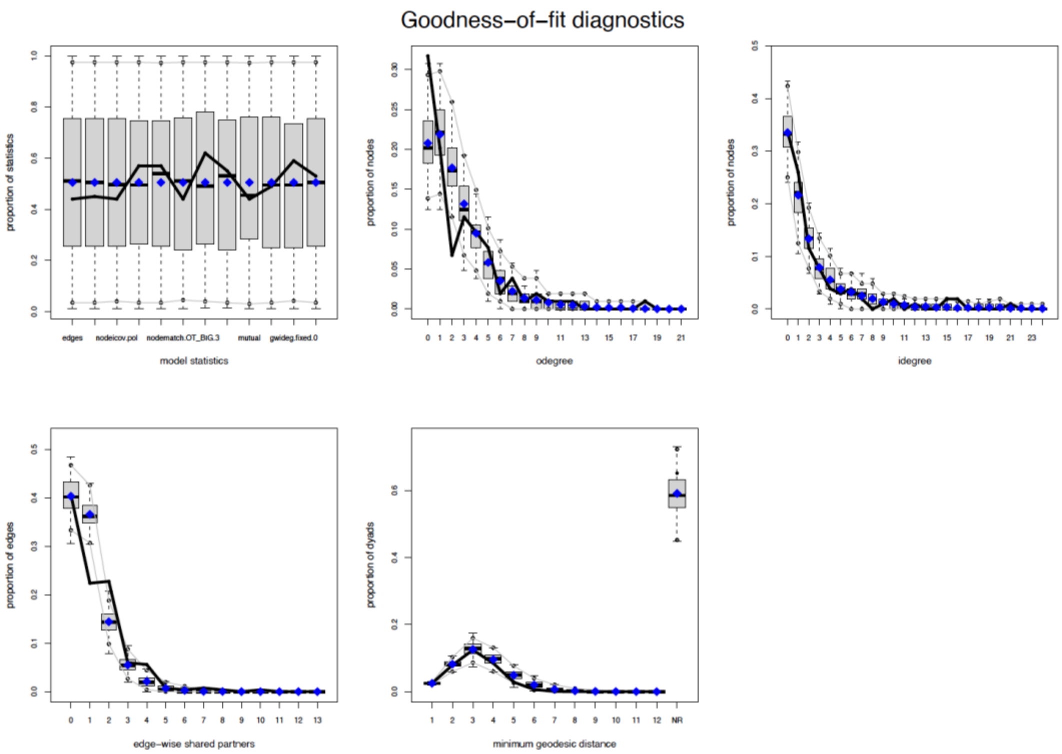
Model 4, Period 41



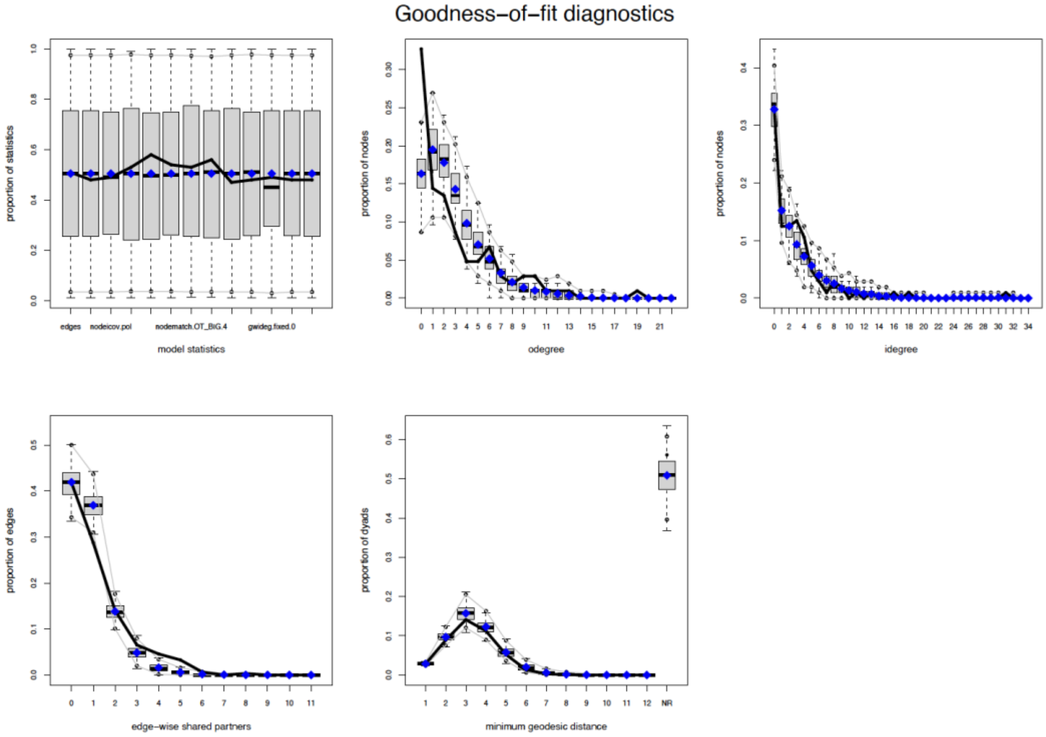
Goodness-of-fit plots, Model 1, Period 32



Model 2, Period 24



Model 3, Period 12



Model 4, Period 41