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Politicians' use of emotional appeals in European democracies

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Chapter 5

Analyzing Political Rhetoric as Networks of Rhetorical Styles

Abstract

In this paper I introduce a novel approach to the study of political rhetoric, using network analysis to model the rhetoric politicians use. Building on the premise that one rhetorical style (e.g. sentiment or narration) alone is insufficient to understand politicians' rhetorical strategies, I explore the connections between various rhetorical styles and their impact on political communication. Utilizing speech transcripts from the UK parliament between 1992 and 2019, I construct unimodal networks of individual rhetorical styles and bimodal networks connecting politicians via their use of rhetoric. My analyses reveal connections between rhetorical styles, and find that factors such as party affiliation, cultural conservatism, gender, and term-end approaching are associated with lower rhetorical distinctiveness. This paper demonstrates the value of treating political rhetoric as a network of rhetorical styles to uncover concealed affiliations, shared beliefs, and alliances that might not be evident using other analytical approaches. The network approach offers new tools for addressing important questions in political communication.

A manuscript based on a revised version of this chapter is currently being prepared for submission to a journal.

From agenda-setting and framing to personalization and populism, politicians use rhetorical styles like narration, sentiment, or repetition to connect to their audience and to persuade them to support their ideas (Charteris-Black, 2011; Cohen, 1995; Holian, 2004; Riker, 1996). For instance, the study of politicians' expressed sentiment gained prominent ground in political communication (e.g. Castanho Silva & Proksch, 2021; Cochrane et al., 2022; Crabtree et al., 2020; Haselmayer et al., 2021). But when politicians give a speech or write a social media post, sentiment is just one of the tools politicians have in their rhetorical toolkit. Focusing only on sentiment can give us a limited view, as emotional appeals can come in different forms like personal stories or critiques, not just through sentiment alone. For example, a politician can combine positive sentiment with telling a personal story to appear more connected to their voters. Or when criticizing a policy proposal of an opponent, a politician can choose to combine negative sentiment with either referring to hard economic facts, or with an illustrative story about how their constituents might be impacted in their daily lives. Just studying the politician's sentiment is likely to fall short of a full understanding their rhetorical strategies. While analyses of political rhetoric have typically been the domain of qualitative and holistic approaches (e.g. Charteris-Black, 2009) – restricting scholars to study only a single rhetoric style and/or small number of cases – recent advances in computational text analysis now allow us to measure many styles of rhetoric at scale (Benoit et al., 2019; Boyd et al., 2022; Hopp et al., 2021; Pipal, Schoonvelde, et al., 2023; Rice & Zorn, 2021; Widmann & Wich, 2022). While this solves issues of scaling and reliability, it does not by itself overcome the analytical shortcomings of studying rhetorical styles in isolation.

In this article, I propose to use network analysis as a new approach to study the rhetorical styles politicians' use. Rhetorical styles are linguistic techniques employed by politicians to persuade, inform, or influence their audience (Fahnestock, 2011). Examples of rhetorical styles include emotionality, hyperboles, ambiguity, complexity, and the use of singular versus plural pronouns. By modeling political rhetoric as a network, we can better align our analyses with many of the theoretical underpinnings of political communication such as framing theory (Entman, 1993; Scheufele, 1999) and the Narrative Policy Framework (Jones et al., 2014; Schlauffer et al., 2022), both of which emphasize the importance of politicians combining rhetorical styles to influence public opinion, shape discourse, and affect policy decisions. The network approach allows for a more comprehensive understanding of how politicians craft messages to resonate with their audience and impact policy outcomes.

In a network analysis, networks consist of nodes (components of a system) and ties (relationships between these components). Networks can also be classified according to the number of node sets included in the network. Unimodal networks consist of only one type of nodes. For instance, nodes can be the individual rhetorical styles a politician uses, and the ties connecting them can indicate the degree to which these styles are

used together. The resulting network thus differs per politician, and allows us to answer questions about their individual use of rhetoric. Unimodal networks can therefore be used to analyze which rhetorical styles go together, or when connections between styles become stronger or weaker. Bimodal networks, on the other hand, consist of two sets of nodes. For instance, politicians (set A) and rhetorical styles (set B) can be two categories of nodes. The resulting network then describes the relations between politicians and rhetoric across all politicians, and allows us to answer questions about the relationship between politicians. Bimodal networks can therefore be used to, for example, analyze how different politicians are from each other in their use of rhetoric, or to examine rhetorical clusters. They help uncover concealed affiliations, shared beliefs, or alliances that might not be evident using other analytical approaches, enabling a deeper understanding of the factors influencing political decision-making, policy development, and coalition formation.

Utilizing speech transcripts of debate contributions delivered in the UK parliament between 1992 and 2019, I illustrate how political rhetoric can be modelled as either unimodal networks of rhetorical styles or bimodal networks connecting members of parliaments via their use of rhetoric. To do so, I measure ten individual rhetorical styles using style dictionaries that have been expanded using a word embedding model of parliamentary language. Constructing unimodal networks of politicians' use of rhetorical styles, I demonstrate how politicians can be characterized by their interplay of styles. With bimodal networks, I show how the network of politicians – constructed from their use of rhetorical styles – evolves over time and electoral cycles. I then show how classic network measures like centrality (i.e. the importance or influence of a node within a network) can be used to describe the rhetorical space, and demonstrate that a new measure of rhetorical distinctiveness can be constructed from centrality measures.

With the first approach, creating unimodal rhetoric networks for each MP on a yearly basis reveals the underlying connection between rhetorical styles, and regression models uncover the associations between political behavior variables and connections between styles. My illustration reveals, for instance, that for MPs of the government party and culturally extreme politicians, the connection between narrative and positive styles are larger. This means that those politicians, whenever they speak positively, they also speak in a more narrative, illustrative way. The illustration also finds that after the Brexit referendum took place, the connection between narrative and negative styles are stronger, i.e. if politicians now speak using narrative language, these speeches are more negative than they used to be.

With the second approach, using bimodal networks to model MP's rhetoric in parliament, I show how rhetorical clusters evolve over time. While often observing a clear divide between government and opposition politicians, this division is sometimes becomes blurred. For instance, while the MPs of the liberal party were rhetorically close to conservative MPs up until 2010, their rhetoric became more closely associated with those of

Labour MPs during their coalition government with the Conservative party in 2010 to 2015, indicating rhetorical distancing. The network approach is a way to identify this pattern. I also use this bimodal network to measure the rhetorical distinctiveness of MPs. Overall the analysis illustrates that distinctiveness typically fluctuates during the electoral cycle, with MPs being less distinct at the beginning and end of the parliamentary term. I further show that female MPs, MPs from culturally conservative parties, and MPs who are about to leave the parliament by the end of the term are less distinct in their rhetoric. Further, MPs are more distinct in their rhetoric after the Brexit referendum took place.

Overall, by employing network analysis on political rhetoric, I uncover the nuanced interplay of rhetorical styles that define politicians' communication. The findings not only shed light on the multifaceted nature of political discourse but also underscore the importance of expanding our analytical toolkit beyond traditional methods to capture the full breadth and depth of political communication.

5.1 Network models of political rhetoric

Politicians put a lot of effort into crafting their arguments to present to the public. They prepare speeches, write social media posts, and rehearse their lines for TV interviews. In these arguments politicians typically don't just lay out their position on an issue or policy, but they typically include rhetorical styles (also called rhetorical devices, rhetorical features, or rhetorical elements). Rhetorical styles are linguistic techniques employed by politicians to persuade, inform, or influence their audience (Fahnestock, 2011). Examples of these styles include appeals to emotions, evaluations of costs and benefits, use of hyperboles, employment of ambiguity or analogies, and references to personal experiences or historical events. The analysis of such styles has been a prominent avenue of research in political communication (e.g. Charteris-Black, 2011; Cohen, 1995; Holian, 2004; Riker, 1996), as well as studies investigating how the usage of these styles influences citizens' attitudes and behaviour (Blumenau, 2021; Jung, 2020; Loewen et al., 2012; Schlesinger & Lau, 2000). But what constitutes the unique package of rhetorical styles that makes up a politician's rhetoric?

Advances in computational text analysis now allow researchers to measure different rhetorical styles at scale. Most prominently, politicians' appeals to emotions – usually in the form of sentiment analysis, i.e. the analysis of positively versus negatively valenced language – have been analyzed (Crabtree et al., 2020; Haselmayer et al., 2021; Pipal, Bakker, et al., 2023). But also beyond sentiment, rhetorical styles like textual complexity (Bischof & Senninger, 2018; Decadri & Boussalis, 2020; Schoonvelde, Brosius, et al., 2019), moral appeals (Graham et al., 2009; Hopp et al., 2021; Sagi & Dehghani, 2014), analytical language (Jordan et al., 2019), or the use of a narrative style (Blankenship

& Robson, 1995; Childs, 2004; Hargrave & Langengen, 2020) employed by politicians have been studied. While there are studies that measure and analyze several rhetorical styles (e.g. Hargrave & Blumenau, 2022), they typically analyze each rhetorical style on its own. This means that studies might measure, for instance, both sentiment and the degree of using personal versus communal language. But instead of analyzing the relationship between these two styles, empirical models are estimated that explain the differences in levels for each style. Which politicians speak more positively? And who speaks with a more communal voice? Without doubt, such analyses provide important insights into how politicians make use of rhetorical styles, but they tell us little about the relationship between them.

Instead of analyzing each style on its own, I propose to treat political rhetoric as a network of rhetorical styles. In such a network, the rhetorical styles politicians use vary in both their levels (i.e. how much of a given style) and connections (i.e. how do different styles go together). With treating political rhetoric as network we can then analyze the interplay between rhetorical styles, reflecting the complex nature of political rhetoric. For instance, framing theory posits that the way an issue is presented (i.e. the "frame") can significantly influence public opinion and policy decisions. Politicians often use a combination of rhetorical styles to create frames that emphasize certain aspects of an issue while downplaying others, ultimately shaping public perception and discourse (Entman, 1993; Scheufele, 1999). Another example is the Narrative Policy Framework which focuses on the role of narratives and storytelling in shaping policy processes and outcomes (Jones et al., 2014; Schlauffer et al., 2022). Politicians often use a combination of rhetorical styles to construct compelling narratives that resonate with their audience's values, emotions, and beliefs, ultimately influencing policy decisions (Shanahan et al., 2011).

In the remainder of this section, I introduce the fundamentals of Social Network Analysis (SNA) and outline how the techniques used in SNA can be used to study political rhetoric. In SNA, networks consist of nodes (components of a system) and edges (relationships between these components). The edge in a network may or may not be directed (having a specific direction from one node to another) and may or may not be weighted (edges are assigned a value to represent the strength of the relationship) (Dalege et al., 2017, p. 529). Networks can be constructed based on different kinds of data, where nodes and edges have a specific meaning. For example, in a social network analysis of a group of friends, each individual would be represented by a node and the edges would indicate the strength of the relationship between each pair of individuals. In a political social network analysis, nodes could represent the individual politicians in parliament, and the edges would indicate the number of times these politicians addressed each other.

Another distinction in social network analysis concerns the types of nodes the network includes. There are two main types of networks based on the number of node sets.

Unimodal networks, also known as one-mode networks, consist of a single set of nodes, where each node can be connected to any other node. An example of this would be a group of people discussing media content. On the other hand, bimodal networks, also known as bipartite or two-mode networks, include two distinct sets of nodes, where connections are only possible between nodes of different sets and not within the same set. An example of this is a network of people who consume different media content (e.g., TV programs), where people are only related to TV programs, but not directly to each other, and TV programs are not related to each other. I will now discuss unimodal and bimodal networks, and their ties to political rhetoric, in turn.

Unimodal networks

The networks analyzed in political science research are often unimodal networks (see Siegel (2011) and Ward et al. (2011) for an overview). Beyond applications in political science and other areas of the social sciences, most network analysis techniques (e.g. measures of centrality or density) have been developed for this type of networks (Wasserman & Faust, 1994). In a unimodal network, only one type of nodes exist, and these nodes are connected to each other via edges (also often called ties). For example, these nodes can be individual people. In unimodal networks we can often directly estimate the connections between the nodes by observing real world connections. For instance, in a network of children in a class, we can ask them if they talk to the other children in the class on a regular basis. This information can be used to directly estimate the connections between children: Those children that talk with each other are connected, and no connection exists between any pair of children that do not talk to each other.

In political science, scholars are, for example, interested in a discussion network between members of parliament (Walter et al., 2022). In this case, individual politicians would form the nodes. We can then measure how often each politician mentions any other politician, the more often politicians address each other, the stronger is their connection. Again, each connection between nodes is measured directly. Unimodal networks have also been used to analyze co-sponsorship patterns of bills in the European parliament (Baller, 2017) and legislators' social relationships Ringe et al. (2013). In political communication and political economy, researchers have used unimodal network analysis to study discussion networks about politics and corporate networks, respectively (Garcia-Bernardo et al., 2017; Song, 2015).

In general, estimating a unimodal network works for all kinds of data, as long as it can be represented as nodes and edges. This process typically involves first identifying a set of nodes (e.g. individuals, organizations) and defining the relationships (edges) between them based on a specific criterion (e.g. communication, collaboration). Next, various statistical or computational methods are used to analyze the structure and prop-

erties of the network, uncovering patterns and insights about the relationships among the nodes. While the nodes in aforementioned applications are often individual actors, networks do not have to be actor networks. For example, unimodal networks have been employed to represent attitudes towards politicians, framing them in a networked structure of attitudes (Dalege et al., 2016; Dalege et al., 2017). Such networks facilitate comparisons between different types of attitude structures. This includes networks that evaluate various politicians (showcasing within-person differences) or networks that highlight different individuals’ evaluations of a single politician (capturing between-person differences) (Dalege et al., 2017; Hevey, 2018).”

Here I propose to use the same logic to construct rhetorical style networks. For instance, if we want to analyze how politicians are using a set of rhetorical styles, we cannot directly observe how each style is connected to all other styles. But instead, using a sufficiently large number of observations (e.g. speeches) and rhetorical measures for each speech, we can estimate these connections by calculating to what degree the use of one style predicts the use of another style. By doing this for many styles, we get a network representation of how a politician uses the entire set of rhetorical styles, thus describing her rhetorical space. Similar to attitude networks, this network does not inform us about how much each rhetorical style is used (e.g. how positive does a politician speak), but it tells us something about the relation between styles (e.g. if a politician speaks very positively, does she also use personal language?). We can then also compare these networks within (e.g. talking about different topics, or speaking at different points in time) or between politicians (two different politicians talking about the same issue). Figure 5.1 present a schematic display of a unimodal rhetorical styles network of a politician, where the connections between styles indicate if they are used together.

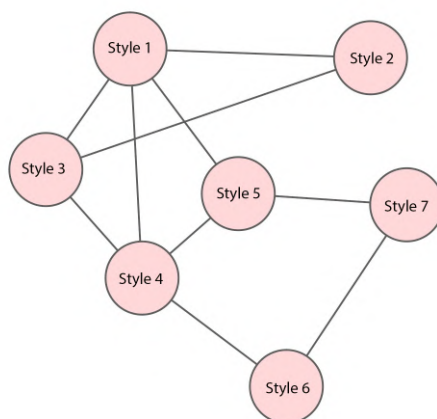


Figure 5.1. Schematic display of a unimodal network of rhetorical styles. Nodes represent rhetorical styles, and edges represent connections between the styles.

Bimodal networks

While social network analysis is often concerned with connections between nodes of the same type (e.g. children in a school class), many applications are in fact reflecting connections between two sets of nodes (e.g. attendance of school children at different extra-curricular events). Such networks are called bimodal or biparte networks. To illustrate this for an MP-rhetoric network of speeches delivered in parliament, the two sets of nodes correspond to the set of MPs and to the set of rhetorical styles. An edge (a connection) between MP_i and $style_j$ exists when an MP speaks sufficiently frequently using the rhetorical style (what sufficiently means is defined below). Importantly, in the bimodal network no connections exist among nodes of the same set, thus MPs are connected only to the rhetorical styles they use.

Once this bimodal network is constructed, we can project the bimodal network onto one type of node. Such a unimodal projection of the bimodal network allows to analyse the relationships between one type of node in respect to the other type. In our case, with an MP-projection of the bimodal network, we can analyse the relationship between MPs in respect to their use of rhetorical styles. This means that with bimodal networks we can reveal hidden connections, alliances, or shared ideologies that might not be apparent through other methods of analysis, allowing us to better understand the underlying factors that drive political decision-making, policy formation, and coalition building.

Figure 5.2 displays a schematic display of a hypothetical bimodal network and its projections on the MP and rhetorical style level. The edges between the nodes in the projections are weighted by the number of neighbours the nodes have in common in the bimodal network. For instance, if two MPs are connected to the same four rhetorical styles in the bimodal network, their connecting edge in the MP projection will have a weight (or strength) of four. If they are only connect to one same style, the have a weight of one.

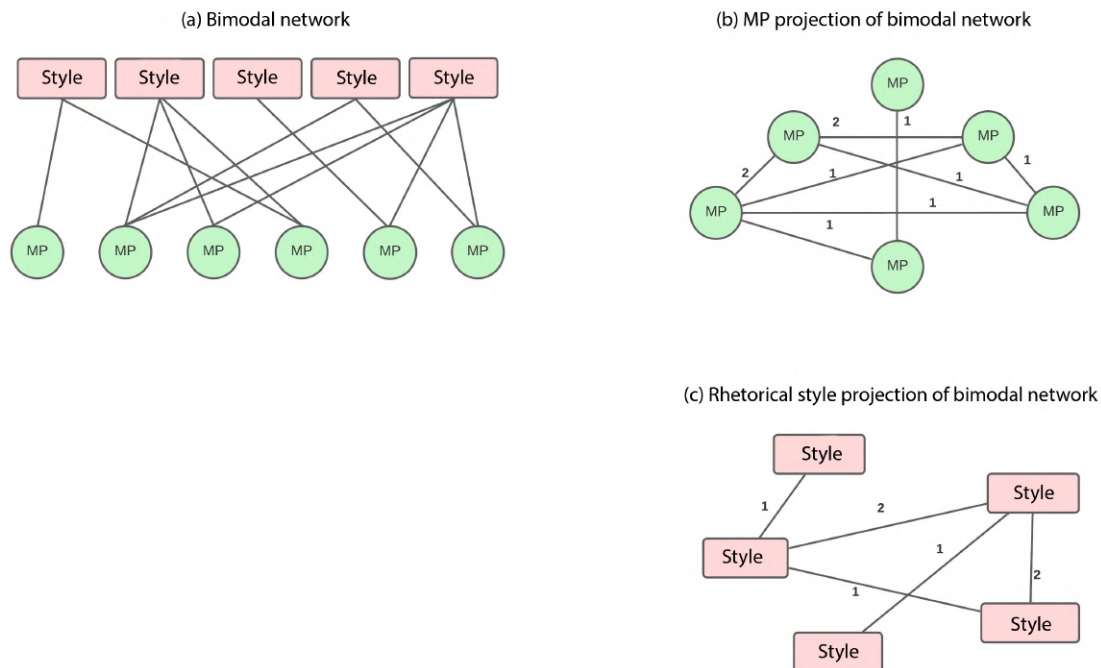


Figure 5.2. Schematic display of a bimodal MP-rhetoric network with unimodal projections. (a) Bimodal network of hypothetical MP-rhetoric network, edges are usage of a specific rhetorical style above a set threshold. (b) Unimodal projection where nodes represent MPs. (c) Unimodal projection where nodes represent rhetorical styles. The numbers in the unimodal projection indicate the strength of the connection, which is based on the number of shared neighbours among two connected nodes in the bimodal network in (a).

5.2 Data and methods

In the remainder of this paper I demonstrate the analysis of political rhetoric as a network of rhetorical styles. To this end I use the transcripts of parliamentary speeches to measure political rhetoric. Specifically, I use the speeches from the House of Commons (HoC) between 1997 and 2019 (Parliament, 2023). In the UK, MPs enjoy a large degree of autonomy regarding the debates to which they contribute, and party leaders exert no control over who participates in a debate, nor over the content of speeches that MPs deliver. The speech data are aggregated so that each document consists of all contributions an MP delivers within a debate (all speeches on a given agenda on the same day). Before measuring each rhetorical style, I filter out speech documents shorter than 50 words and exclude contributions by the Speaker of the HoC, since these speeches are predominantly procedural. Such filtering is standard practice in computational analyses of parliamentary speeches (e.g. Hargrave & Blumenau, 2022; Schoonvelde, Brosius, et al., 2019).

Measuring rhetorical styles

Before constructing the rhetorical networks, we need to measure the rhetorical styles that comprise the network. As an illustration I construct the rhetorical space from ten rhetorical styles that have been used in previous work on parliamentary rhetoric (Hargrave & Blumenau, 2022). Following the procedure from Hargrave and Blumenau (2022), I measure these styles for all speeches delivered by MPs in each debate. Six styles (emotional, positive, negative, aggressive, factual, narrative) are measured using a GloVe word embedding model (Pennington et al., 2014) estimated on the full corpus of speeches, which has been extensively validated on English language parliamentary proceedings (Rodriguez & Spirling, 2022). To calculate a score for each word for each rhetorical style, I use seed dictionaries that serve as anchor points in the embedding model, and score each word in the corpus using the cosine distance to these anchor words (see Rheault et al., 2016; Rice & Zorn, 2021). Two styles (personal and communal) are measured using simple dictionaries of first-person singular (personal) and plural (communal) pronouns. The remaining two styles are measured differently. Complexity is measured with the automated readability index (ARI) using the `quanteda.textstat` R-package. Repetition is measured as the usage of identical words and word patterns within a debate (all speeches on a given agenda on the same day) using the compression rate of a lossless text compression algorithm (`gzip`). All style measures have been extensively validated against human coding in Hargrave and Blumenau (2022), with strong positive correlations between the automated measures and human judgment.

5.3 Application 1: Using unimodal networks to study connections between rhetorical styles

Constructing and comparing rhetorical style networks

The estimation of an unimodal rhetorical style network from the data is using a graphical lasso regression (van Borkulo et al., 2014). This technique involves examining the relationships between all variables in the dataset while applying a regularization process to address the issue of multicollinearity, which occurs when variables are highly correlated (Friedman et al., 2008). The best regression model is chosen using the extended Bayesian information criterion (EBIC) to balance model complexity and goodness of fit (Epskamp, 2016). Whether the connections between nodes can be understood as causal links depends on the assumptions underlying the data (Dalege et al., 2017). Generally speaking, the edges represent the degree to which the connected variables predict each other, while all other observed variables are held constant. Such unimodal networks can then describe the pattern of predictive relations in a data-set or to represent the correlation structure

of the data (Epskamp et al., 2012).

To demonstrate this approach, I estimate the rhetorical style network of Theresa May, who served both as a Member of Parliament and as Prime Minister, using the measures detailed in the previous section. In total, Theresa May participated in 762 debates, 607 as a Member of Parliament, and 154 as Prime Minister. Separating the data by her Member of Parliament / Prime minister status and following the procedure described above results in two networks of her rhetorical styles as shown in figure 5.3. The left panel shows her rhetorical styles network from her time as a member of parliament (before July 2016), the right panel shows the same network when she was prime minister (07/2016 - 07/2019). In this visual display, thicker lines indicate stronger connections between two styles. Blue (red) lines represent a positive (negative) relationship. Overall, we can see that some strong connections between her rhetorical styles exist already during her time as Member of Parliament (left panel), and that those connections became even stronger when she became Prime Minister (right panel). For instance, her negative rhetoric is strongly connected to using more aggressive and emotional rhetoric, while her positive rhetoric is strongly connected to using more narrative rhetoric. And when she speaks with narrative rhetoric, her use of complexity decreases.

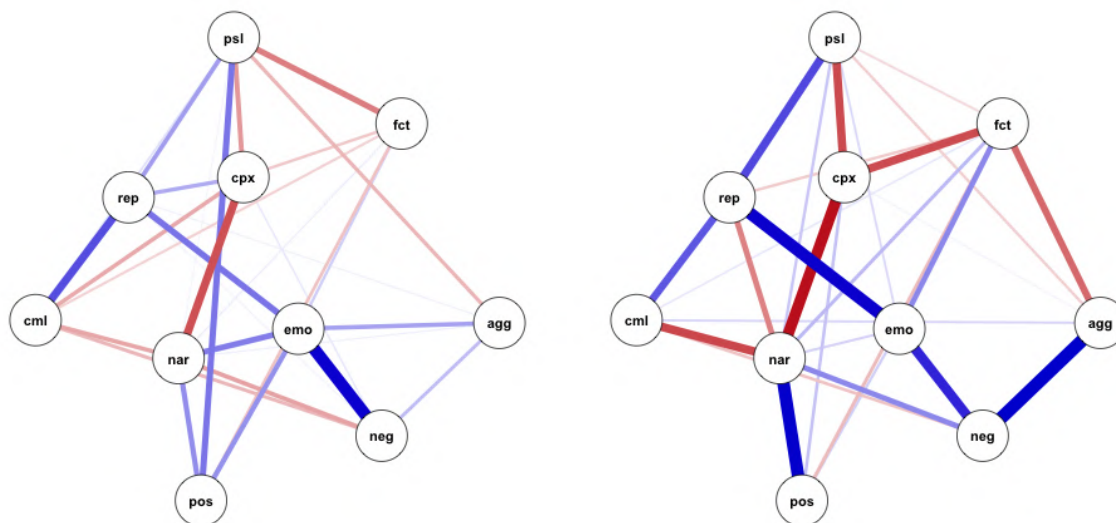


Figure 5.3. Rhetorical style networks of Theresa May’s speeches in parliament. Left panel: style network of Theresa May as member of parliament. Right panel: style network of Theresa May as prime minister. Blue (red) lines represent a positive (negative) association between rhetorical styles. Thickness of lines indicates edge strength. Full names of styles abbreviated in figure (agg: aggression, cml: communal, cpx: complexity, emo: emotionality, fct: factual, nar: narrative, neg: negative, pos: positive, psl: personal, rep: repetition).

Studying these networks allows us to explore how the associations between rhetorical styles differ between politicians or change over time, providing valuable insights into the

dynamics of political communication. This can reveal how politicians subtly adapt their rhetoric, either to differentiate themselves from their party or to align with evolving political landscapes, without necessarily altering the substance of their messages. To formalize this comparison beyond visual eyeballing, we can use network analysis methods to compare the two networks from Theresa May’s times as a Member of Parliament and as Prime Minister with each other. For instance, the Network Comparison Test (van Borkulo et al., 2016) uses permutations to test for differences between two networks for each edge strength. Using this test reveals that, using a significance threshold of $p < 0.05$ and a two-sided test, out of 81 possible edges, six edges significantly changed between these two time periods, indicated by a difference (d) in edge strength: the connection between negative and aggressive rhetoric ($d = 0.38$, $p < 0.01$), positive and narrative rhetoric ($d = 0.29$, $p < 0.01$), negative and narrative rhetoric ($d = 0.32$, $p < 0.01$), aggressive and factual rhetoric ($d = -0.24$, $p < 0.01$), positive and personal rhetoric ($d = 0.21$, $p = 0.01$), and between factual and personal rhetoric ($d = 0.15$, $p = 0.04$). Substantially, these results suggest that the relationships between certain rhetorical styles have evolved over time. For instance, the connections between negative and aggressive rhetoric, positive and narrative rhetoric, and negative and narrative rhetoric have all strengthened, indicating that these rhetorical styles are now more likely to be used together. Conversely, the connections between aggressive and factual rhetoric have weakened, suggesting that these styles are now less likely to be combined. The evolving interplay of rhetorical styles not only signals shifts in political communication, but also calls for an exploration of the factors associated with these connections.

Correlates of connections between rhetorical styles

So far my illustration has focused on comparing just two rhetorical style networks. However, with larger data sources, there are numerous potential comparisons and analyses to explore. For example, rather than just examining the debate observations of a single politician, it is possible to estimate a style network for the entire parliament based on all debates, or to calculate separate networks for each party in parliament. Additionally, going beyond the comparison of two networks, multiple rhetorical style networks can be estimated (e.g. one for each politician per year), which enables an investigation into the socio-demographic and political factors that may predict connections between rhetorical styles.

To demonstrate such analysis, I separate the data on a speaker-term-year basis and estimate a rhetorical style network for each of these observations. This is important, because separating only by year would lead to overlap between parliamentary terms (e.g. 2017 is only an election year for speeches given in the 2015-2017 term, but not for those in the 2017-2019 term). Because estimating networks from a handful of observations is

not meaningful (Epskamp, 2016), I use a minimum threshold of 50 debates per speaker-term-year combination to be included in the analysis. This results in a final sample of 2,255 observations from 587 individual MPs (41.3% of all MPs).

For this illustration, I explore the correlates of edge strengths in the rhetorical style network, i.e. how strongly rhetorical styles are connected. To this end, I estimate a series of OLS models using the the edge strengths of three selected connections between styles. These connections are between narrative and positive rhetoric, narrative and negative rhetoric, and narrative and emotional rhetoric. While these connections serve as an example, researchers should tailor their analyses to the connections directly relevant to their research objectives. I include a series of commonly used legislative behavior indicators as independent variables. At the individual MP level, I include the number of debates a speaker has participated in, the number of years in parliament an MP has served, their gender, age, if they joined or left the parliament in a given term, and whether they are a backbencher or not. At the party level, I consider whether it was part of the government or opposition. I also include measures of economic left-right and cultural progressive-liberal ideology as well as the respective ideological extremism scores. The data for these variables come from the Comparative Manifesto Project and are measured at each election. On the parliamentary term level, I include a measure of party system polarization. Because of repeated observations, the standard errors are clustered at the level individual politician.

Each panel in figure 5.4 displays the results of OLS models explaining the connection between two rhetorical styles.

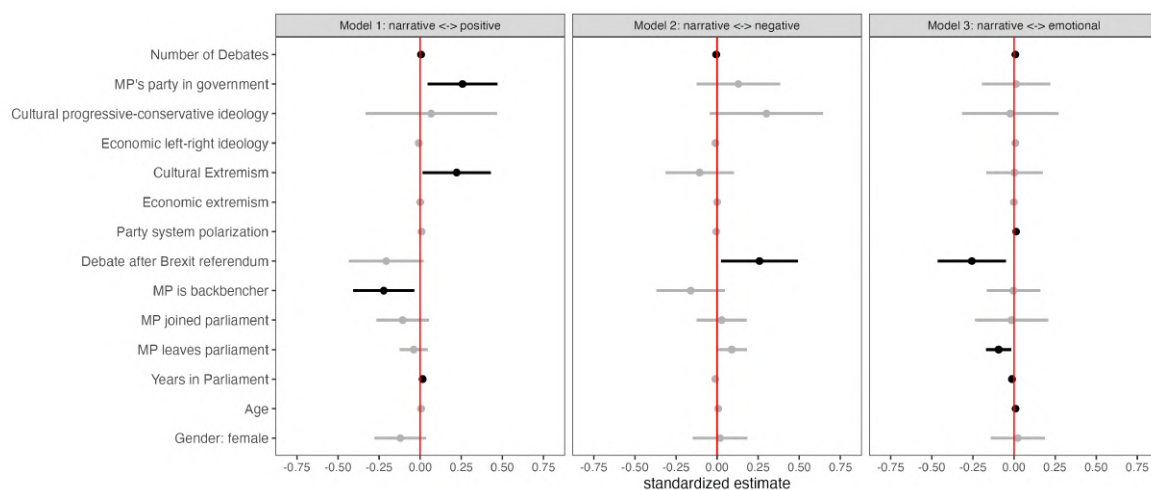


Figure 5.4. OLS models explaining connections between styles in rhetorical styles networks. The dependent variable is the estimated edge strength between two rhetorical styles. OLS models with robust standard errors clustered at the individual MP and parliamentary term fixed effects (nobs = 2,255, nclusters = 587. Only observations that are constructed from a minimum of 50 speeches are included in the analysis. Dots are point estimates, bars indicate the 95% confidence intervals.

In the left panel, the dependent variable is the strength of the connection (edge weight) between narrative and positive rhetoric. Based on the results from this model, I find that MPs who are members of a government party have a stronger connection between narrative and positive rhetoric ($b = 0.26, p = 0.02$). Similarly, MPs who are positioned more extremely on the culturally liberal-conservative scale also show a stronger link between these rhetorical styles ($b = 0.22, p = 0.04$). Conversely, backbencher MPs exhibit a weaker association between narrative and positive rhetoric ($-0.22, p = 0.02$). In the center panel, the dependent variable is the connection between narrative and negative rhetoric. When a speech is given after the Brexit referendum, the connection between narrative and negative rhetoric is stronger than before when the speech is given before the Brexit referendum ($b = 0.26, p = 0.04$). The right panel shows the results for the connection between narrative and emotional rhetoric. Here speeches given after the Brexit referendum tend to show a weaker connection ($b = -0.26, p = 0.02$) between these styles. The same is true for speeches given by leavers who show a weaker connection between narrative and emotional rhetoric ($b = -0.09, p = 0.02$). However, an overarching observation is that while some variables do manifest statistically significant effects, a comprehensive understanding of the strength of rhetorical style connections remains elusive. This suggests that the relationships between rhetorical styles could be influenced by a multitude of factors, some of which might not have been captured in this analysis, underscoring the complexity of political communication.

Through this analysis of rhetorical style networks, I have identified patterns in Theresa May's speeches as a Member of Parliament and as Prime Minister, and also discovered broader trends among all MPs. These insights highlight the intricate relationships between different rhetorical styles and how they can be influenced by various factors. With this foundation set, I now turn towards the bimodal analysis for further insights into how politicians are connected via their rhetoric.

5.4 Application 2: Using bimodal networks to study rhetorical distinctiveness

Constructing the bimodal MP-rhetoric networks

With bimodal MP-rhetoric networks we can now analyze how MPs are connected to each other via their use of rhetorical styles. While I measure the use of each rhetorical style for each MP, that is each MP is to some degree connected to each rhetorical style, I only include in my analysis those rhetorical styles that each MP used significantly more often than the average of all MPs within the same parliamentary term. For instance, an MP is considered to use the "aggressive"-style if he speaks much more aggressive than the

average MP in a given parliamentary term. This procedure, known as thresholding, is done to thin out dense networks that would make analysis and interpretation impossible. Because most MPs are (to some) degree using every rhetorical style, this would otherwise result in complete subgraphs for most MPs (where every MP is connected to every style).

To construct the bimodal network of MPs and their usage of rhetorical style, I use an "above-average"-threshold for creating an edge between an MP and a given rhetorical styles. Such thresholding is a common practice in social network analysis and serves two purposes: indicating relationship strength by creating ties based on multiple attribute mentions, and "thinning" overly dense networks for feasible statistical analysis (Cranmer & Desmarais, 2011; Fowler, 2006). In practice, for each MP I check if her measure of a rhetorical style is at least one standard deviation above the mean. Compared to the unimodal rhetorical style network, the connections between MPs and rhetorical styles are directly measured. There is therefore no minimum sample size required for creating the network.

MP projections of the MP-rhetoric network

Figure 5.5 presents the resulting MP projection of the bimodal MP-rhetoric network following the procedure described above. The colours reflect the parties each MP belongs to. The nodes (MPs) are scaled to their degree centrality in the network, that is how connected their rhetoric is to other MPs. The fact that all nodes have a connection to the network results, as described, from the fact that most MPs use most rhetorical style to some extent, so for each MP there is at least one style she is using more often than the average MP. There are however a few MPs in the 51st (1992 - 1997) and 52nd (1997 - 2001) parliament that are much weaker connected to the network than is the case in the subsequent parliaments. It is evident that party affiliation is one of the main factors in describing the communities of the network. But while the network is structured by party affiliation to a large degree (as nodes of the same color tend to cluster together), this is not equally the case for all parliaments. A notable exception is the rhetoric of LibDem MPs (orange). Typically clustering near the Conservative party (blue), their alignment during the 2010-2015 term, when in government with the Conservatives, became more dispersed, with many gravitating towards Labour MPs (red).

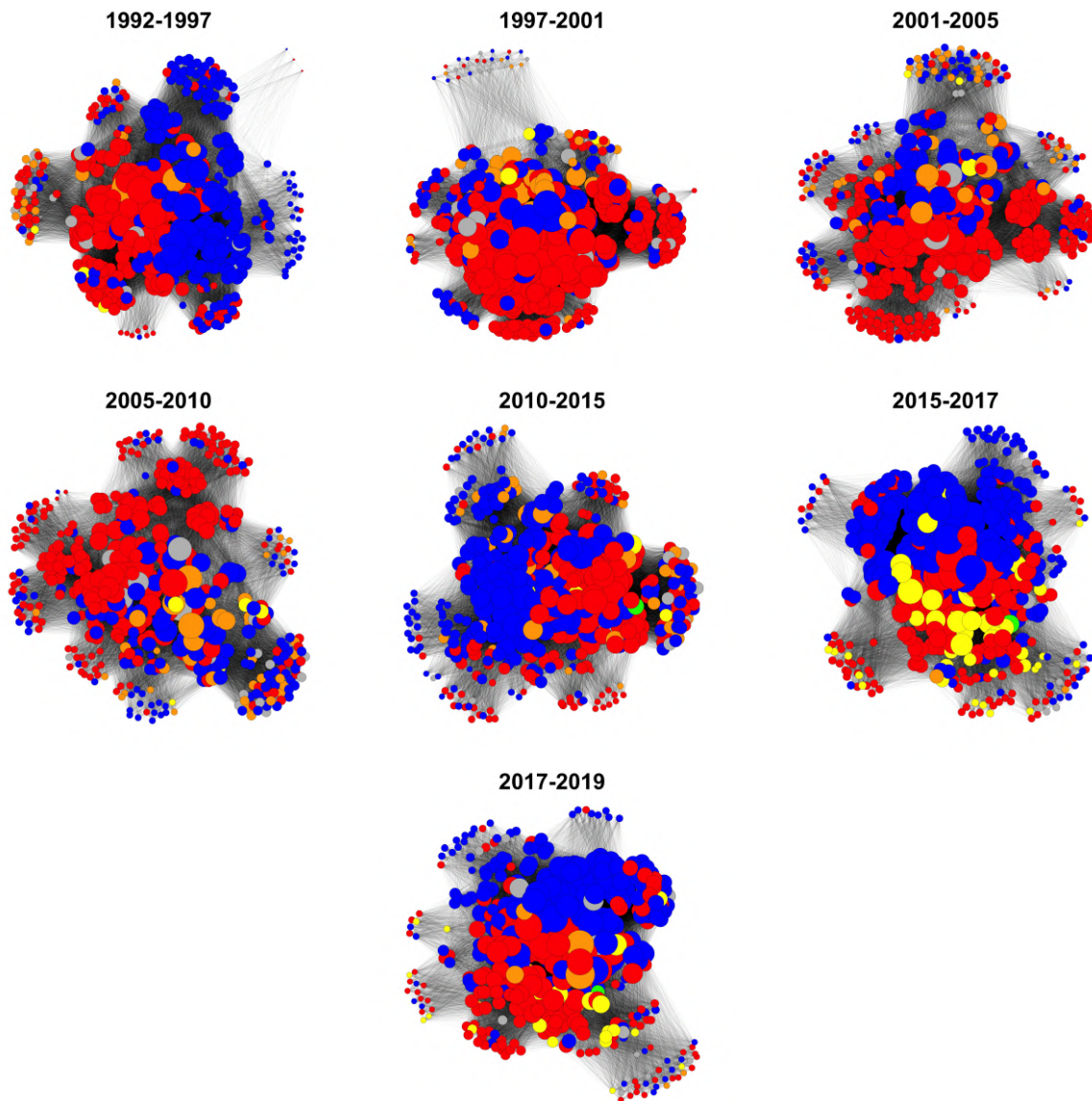


Figure 5.5. MP networks of 51st to 57th parliamentary. Network visualisation reflects the MP-projection of the bimodal MP-rhetoric network. Node size is equivalent to the degree centrality of each MP within the network. Colors reflect the UK party colors.

But how does the network change within a parliamentary term? Figure 5.6 presents the same MP projection, but for each year of the 55th parliament between 2010 and 2015. Overall, we can see a changing distance between network communities over the course of the term. In the initial year, all MPs appear densely clustered, suggesting a shared use of rhetorical styles. As the parliamentary term progresses, their rhetoric becomes notably more diverse (as seen in the panels of the years 2011 - 2013). Yet, as the term concludes, similarities in rhetoric reemerge. Observing the connection between the MPs of the Conservative party (blue) and LibDems (orange) throughout their government tenure, the visual display indicates a marked diversification in their rhetoric during the

government’s midpoint. Unlike the conservative MPs, the liberal MPs never coalesced into a distinct community in the network. While conservative MPs often exhibited a unified voice, the same cannot be said for the liberal party.

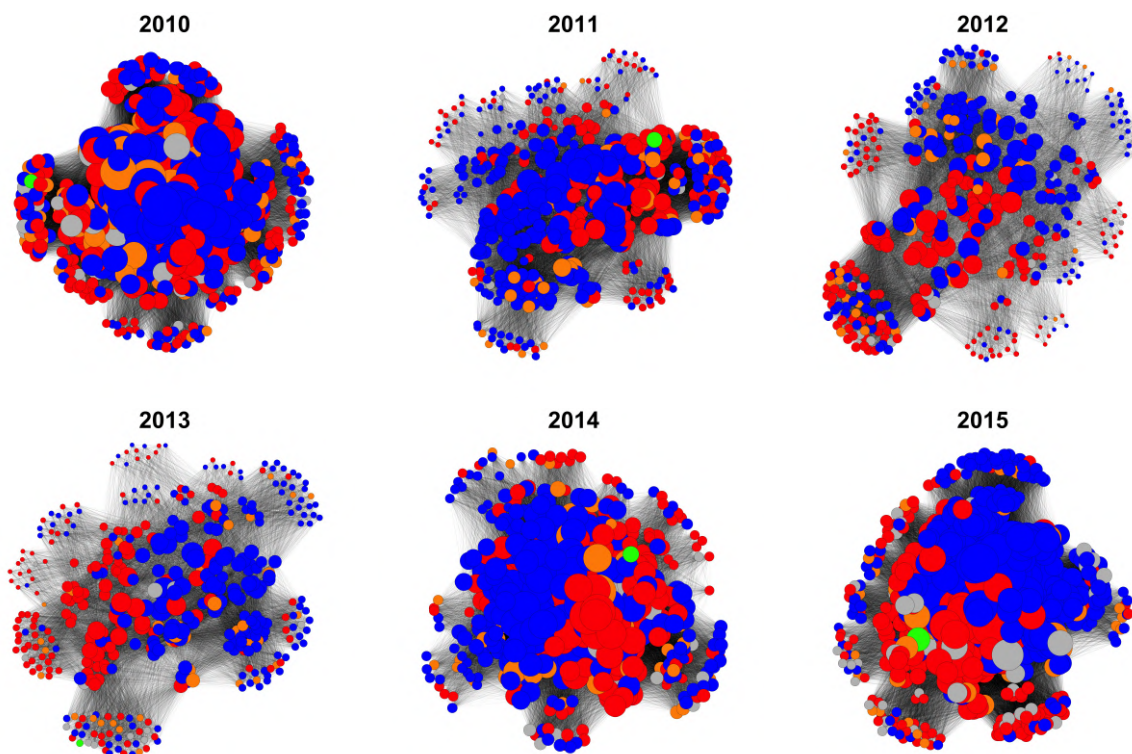


Figure 5.6. MP networks for 2010-2015 parliament. Network visualisation reflects the MP-projection of the bimodal MP-rhetoric network. Node size is equivalent to the degree centrality of each MP within the network. Partys indicated by colors (Blue: Conservative Party, red: Labour Party, orange: Liberal Democrats).

Analyzing rhetorical similarity and distinctiveness

Another novel use of this MP-projection of the MP-rhetoric network is to create a network based measure of rhetorical distinctiveness. This involves examining connectivity variations, specifically assessing the extent to which MPs share rhetorical styles with their peers. In this MP-projected network, an MP’s connectivity to other MPs indicates how similar their usage of rhetorical styles is. The inverse of this measure then indicates the distinctiveness of an MP in respect to her rhetoric. This is formally done by using the network measure of degree centrality of each MP. Figure 5.7 displays the average degree centrality for each year by newcomer status, with higher values indicating more rhetorical similarity. Overall, this picture confirms the intuition from Figure 5.6: as the parliamentary terms go on, MPs become more distinctive in their rhetoric. When the terms come to an end and elections are ahead, they again move closer in their rhetoric. The only time we don’t observe this trend is during the last two parliaments after the Brexit referendum

that resulted in snap elections. Regarding differences between newcomers and established MPs, it is only in the 2010-2015 parliamentary term that we can see big differences. In the beginning of the term, newcomer MPs speak more more distinctively than their established colleagues (as indicated by a lower degree centrality in 2010 for newcomer MPs (blue) compared to established MPs (red)), but within one year this difference is gone. Towards the end of the term all politicians increase their distinctiveness again, and but without difference between newcomers and established MPs.

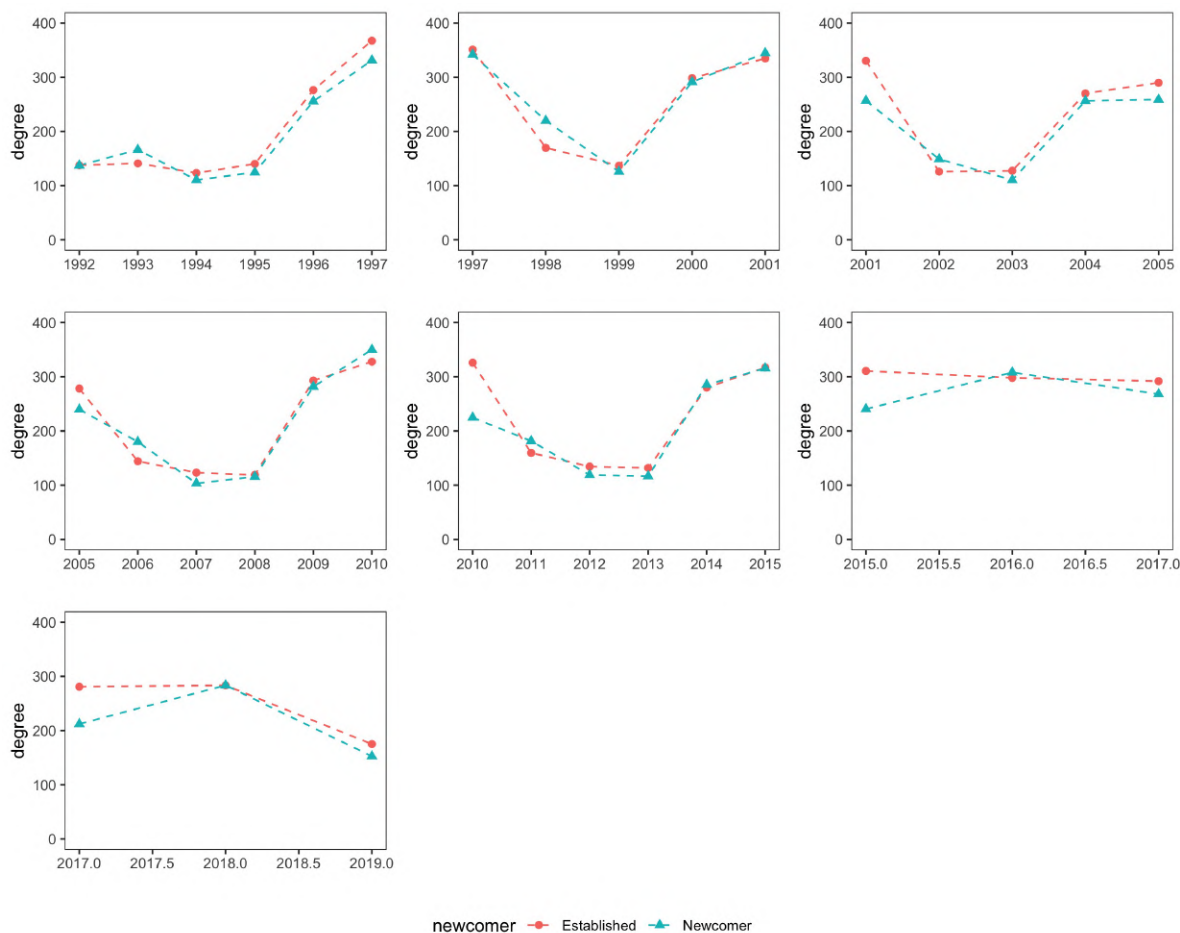


Figure 5.7. Average degree centrality of MPs. Time series of the average degree centrality of MPs by newcomer status (established MPs in red, newcomers in blue). Higher values indicate more connections to other MPs.

Comparison with other measures of distinctiveness

How does this new measure of rhetoric distinctiveness of MPs compare to alternative measures of distinctiveness? Specifically, how does this new measure of rhetorical distinctiveness based on individual rhetorical styles compare to measures based on textual (dis-)similarity? In this section I compare the distinctiveness scores from my network model with the scores obtained by following the procedure from Huang et al. (2020). Huang and colleagues develop a model of "author style" based on stylometry and the

word use frequencies of MPs. While such approaches usually try to predict the authorship of a new text given a set of labelled texts, they adopt this logic to calculate predictions of "authorship differences". For instance, if the predicted authorship probabilities for the same text differ substantially between two speakers, then it follows that these speakers are far apart in their "author style".

Importantly, their approach (and all other approaches looking at textual similarity), measures something substantially different from the network approach. Textual similarity measures pick up on what is said, while the network approach based on measures of rhetoric styles picks up on how it is said. For example, let's look at two speeches given by politician A and politician B. Politician A says "Based on my experience, this is fantastic.", while politician B says "Based on this report, this is fantastic". A model based on textual similarity measures would ascribe a pretty low difference score between the two politicians, since two thirds of their vocabulary is identical. The rhetoric network model, however, would give them a pretty high difference score, because the positive statements are used in combination with a personal story (politician A) or a factual statement (politician B).

I now compare these two measures for all MPs who spoke in the 2010-2015 parliamentary term (41,745 speeches, 636 MPs). I adopt the procedure outlined by Huang et al. (2020) to compute the distinctiveness measure based on textual similarity, utilizing their R-package *stylest*. For vocabulary pruning, i.e. eliminating infrequently used words, I adhere to the methodology they detail in their application (Huang et al., 2020), establishing an optimal cutoff point and retaining the top 20% of words in the vocabulary. The remaining vocabulary is then used to estimate the distinctiveness of each MP. This is because otherwise the model is heavily driven by words that are used by a single author once or twice.

For my network measure of distinctiveness, I measure the rhetoric styles as described above, and construct a bimodal network using these speeches. Using the MP-projected network, I then calculate the degree centrality of each MP (intuitively: to how many other MPs are they similar in their usage of the styles). The reverse of this measure is their distinctiveness. Both scores are rescaled to range from 0 to 1. As expected, the two measures capture something different, and there is no correlation ($r = -0.03$, $p = 0.50$) between the two measures. A visual display of this comparison is presented in appendix 7.4.

Correlates of rhetorical distinctiveness

To explore the correlates of rhetorical distinctiveness, I again aggregate the data on a speaker-term-year basis and calculate MPs' distinctiveness for each of these observations (similar to figure 5.7). These distinctiveness scores are the dependent variable in the

subsequent analysis. As independent variables I include the same set of variables as in the previous application. This includes the number of debates a speaker has participated in, the number of years in parliament an MP has served, their gender, age, if they joined or left the parliament in a given term, and whether they are a backbencher or not. At the party level, this includes whether an MP’s party was part of the government or opposition. I also include measures of economic left-right and cultural progressive-liberal ideology as well as the respective ideological extremism scores, using data from the Comparative Manifesto Project (Volkens et al., 2019). On the parliamentary term level I include a measure of party system polarization using the same data source. I z-scale all continuous variables.

Figure 5.8 displays the results of an OLS model explaining rhetoric distinctiveness. Analyses including a leaver-term interaction and results based on a multilevel model are presented in appendix 7.4.

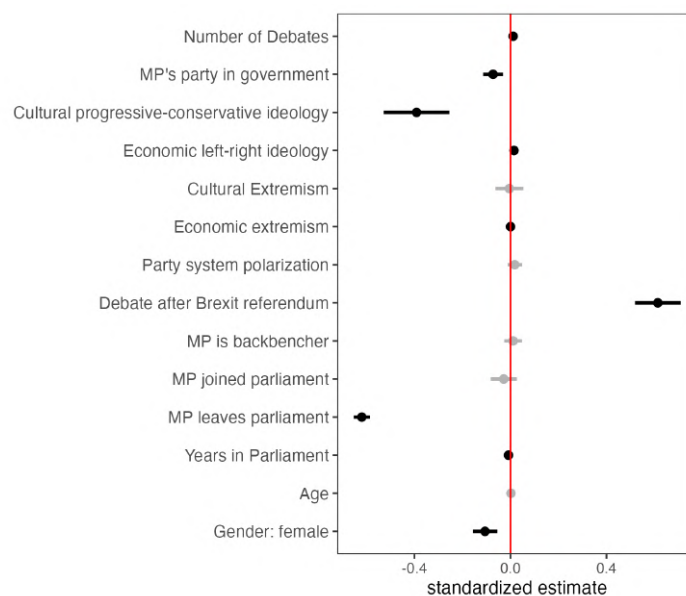


Figure 5.8. OLS model explaining rhetoric distinctiveness. Rhetoric distinctiveness is the reversed degree centrality in yearly MP-projections of the MP-Rhetoric network model. Continuous variables have been standardized. OLS with robust standard errors clustered at the individual MP and parliamentary term fixed effects (n obs. = 16,841, n clusters = 1657). Dots are point estimates, bars indicate the 95% confidence intervals.

What factors explain rhetorical distinctiveness in the UK parliament? Being culturally conservative is strongly associated with a lower degree of distinctiveness ($b = -0.39$, $p < 0.01$). Leaving the parliament at the end of the current parliamentary term is also associated with a lower degree of distinctiveness ($b = -0.62$, $p < 0.01$). Negative, but much weaker, associations are also found for female MPs compared to male MPs ($b = -0.11$, $p < 0.01$) and MPs of government parties compared to MPs of opposition

parties ($b = -0.07$, $p < 0.01$). The only strong positive association concerns the timing of speeches: MPs tend to be more rhetorically distinct after the Brexit referendum compared to the period before the Brexit referendum ($b = 0.61$, $p < 0.01$).

Across multiple parliamentary terms, the analysis of the bimodal MP-rhetoric network highlights the nuanced ways in which rhetorical styles define and differentiate MPs. Party affiliation largely structures the network, with notable deviations in some terms. The distinctiveness of an MP's rhetoric, captured through their network position, evolves throughout a term, hinting at strategic adjustments. Comparisons with textual similarity measures further underscore the unique insights offered by the network approach. Thus, while many factors may influence an MP's political rhetoric, viewing it through the lens of a bimodal network offers revealing insights into parliamentary discourse dynamics.

5.5 Discussion

In this paper I introduce a network model of political rhetoric. Instead of measuring and analyzing rhetorical styles individually, I show how political rhetoric can be analyzed as a network of rhetorical styles. Borrowing tools from network analysis, my empirical demonstration illustrates that moving beyond analyzing styles individually opens new avenues of enquiry. While theories of political communication often implicitly assume an interplay between different rhetorical styles, analyses are often limited to studying one or a handful of styles separately. The network approach comes closer to reality.

In the unimodal network model of political rhetoric, individual rhetorical styles are connected by the degree they are used together. Using this model allows researchers to answer questions about the interplay of rhetorical styles on the individual level. With the bimodal network model of political rhetoric, individual politicians are connected to each other via their usage of styles. This allows researchers to answer questions about the relationships between politicians in respect to their rhetoric. Both models better reflect the interconnected nature of political rhetoric. Politicians do not use one style alone, but can choose from a set of combinations of style to create their rhetorical strategy.

In the empirical illustration, I showcase how networks of political rhetoric can be set up and analyzed. It is important to highlight that the selection and measurement of styles used to create the rhetorical space are by no means exhaustive or uncontested. While these measures are based on previously studied styles (e.g. Bischof & Senninger, 2018; Decadri & Boussalis, 2020; Hargrave & Blumenau, 2022; Hargrave & Langengen, 2020), they mainly serve as a selection of styles for the purpose of illustrating the network approach. How many and which specific styles should be included, and how they are measured, depends on the specific research questions and theories. For instance, studies investigating the process of political personalization might be more interested in connecting different styles related to pathos, i.e. expressive descriptions, personal stories, and

emotional language. Other studies interested in analyzing politicians' moral language might be more interested in connecting styles related to values and credibility, to name a few.

Overall, the network approach can be used to study a wide range of questions related to rhetoric. Compared to a traditional approach that looks at each rhetorical style by itself, the network approach is a more insightful reflection of the complex rhetoric space used in politics, and allows to answer new questions in political communication. For instance, researchers can use this approach to analyze how the rhetoric of individual politicians changes throughout their career. Using a network of their individual rhetoric, they can track their use of rhetoric over time to see if they are subject to professional norms that put limits on their individual style as they climb up the political ranks. The network approach also allows researchers to study larger networks of rhetoric over time. Using bimodal networks, studies could engage in longitudinal analyses of political rhetoric. Who are the rhetorical influencers who shape political discourse? What impact do landmark events like economic crises or wars have on political rhetoric? And who leads the change, and who follows suit?

While the network approach to political rhetoric treats the interplay of rhetorical styles seriously, this approach is not without limitations. First, the estimation procedures to construct unimodal rhetorical networks are quite data hungry. Depending on the number of nodes (i.e. rhetorical styles) included in the network, unimodal networks require a minimum number of observations (e.g. political speeches or social media posts) per unit of analysis (e.g. per politician). Depending on the particular research questions, such amounts of data are often not possible to obtain. For instance, most members of parliament don't speak that often in parliament during the course of a year, let alone on a specific policy issue. The more granular the unit of analysis is, the more problematic this data requirement becomes. Second, like all quantitative models, the network approach to political rhetoric is an abstraction from reality. While they can uncover patterns across a large number of cases, researchers interested in the particularities of specific cases are still encouraged to augment their quantitative analyses with with qualitative approaches.

To conclude, studying political rhetoric as a network of rhetorical styles is a crucial step forward in moving beyond the conceptual shortcomings of many analyses of rhetoric in politics.