DRAFT Measuring Polarization and Conflict in German Parliament - *A Comparison and Evaluation of Techniques using Text-as-Data*

Lukas Birkenmaier

Master's Thesis
Summer 2021
Centre for Interdisciplinary Methodologies (CIM) - Warwick University
Supervisor: Tessio Novack
Word Count: TBA

Abstract

TEXTTEXTTEXT *Here comes the reserach question?* TEXT TEXT TEXT

Key Words: Political polarization, parliamentary debates, natural language processing, sentiment analysis, German Bundestag

Acknowledgement

Acknowledment> I Want to thank X and Y AND Z

Contents

List of Tables

List of Figures

List of Abbreviations

DIP . . . . Documentation and Information System for Parliamentary Materials of the German Bundestag
IfSG . . . . Infektionsschutzgesetz
MP . . . . Member of Parliament
NLP . . . . Natural Language Processing
MLP . . . . Multi-layered Perceptron

1. Introduction

"Some Fancy Quote."

- The guy who did it,

In recent years, scholars have observed a worldwide renaissance of political politicization and polarization. Fostered by the ongoing globalization, economic and ecologic crises as well as the disruption of the media industry, divisions among citizens across countries are growing sharper (Goldberg, van Elsas, and Vreese 2020). For instance, in a recent survey from Pew Research Center (2019), 85 per cent of US respondents stated that the tone and nature of political debates has become more negative in the last years. Likewise, data from the V-Dem Institute (2019) shows that nearly all EU societies have become more polarized in the twenty-first century compared to previous time periods. Ultimately, this trend does not only reflect itself in the growing support of populist parties and politicians, but also more individual feelings of partisanship and emotional distance to arguments contrary to someone's own position (Galston 2018).

When humans read text, they do not see a vector of dummy variables, nor a sequence of unrelated tokens. They interpret words in light of other words, and extract meaning from the text as a whole. It might seem obvious that any attempt to distill text into meaningful data must similarly take account of complex grammatical structures and rich interactions among words. The field of computational linguistics has made tremendous progress in this kind of interpretation. Most of us have mobile phones that are capable of complex speech recognition. Algorithms exist to efficiently parse grammatical structure, disambiguate different senses of words, distinguish key points from secondary asides, and so on. https://www.nber.org/system/files/working$_{p}apers/w23276/w23276.pdf$

In order to better understand this phenomenon, researchers can rely on previous research and theories on public discourse, policy making and intra-party conflicts (QUELLEN!!). However, crucial methodological challenge has always been the measurement of political polarization. Hence, researchers have relied on different methods, ranging from XX to XX to XX. Starting with the , however, a new field of research, based on NLP techniques, has emerged and gained popularity in the last few years. Often, measurements of political polarization are studies in national parliaments, which are the primary arenas for political conflicts and debates (Wendler, 2014). Text as data

In order to develop and test theories of

Definition: Polarization as a state refers to the extent to which opinions on an issue are opposed in relation to some theoretical maximum (Dimaggion 1996).

Wichtigkeit und Problem)deshalb Forschung (Sawhneij)

My analysis relates most closely to recent work by (Goet 2019). He uses text from the Congressional Record to characterize party differences in language from the late nineteenth century to the present. However, he validates his findings

The remainder is as follows: the following chapter 2 introduces the relevant research on political polarization and its relation to text-as-data approaches. Chapter 3 then presents the systematic literature review on the most relevant techniques to measure parliament polarization using parliamentary transcripts. The research design is explained in chapter 5, before chapter 6 and chapter 7 present the results and the discussion, respectively. Chapter 8 completes the dissertation with concluding remarks.

2. On the Relevance of Measuring Political Polarization

"Hatred, anger, and violence can destroy us: the politics of polarization is dangerous"

- Rahul Gandhi,

A large body of literature exists, covering various aspects of political contestation and polarization. Rather than trying to provide an extensive overview over this field, I subsequently aim to shed light on the relevance of measuring political polarization for political science research. Doing so, I will first provide a concise overview over the impact of political polarization on democratic political systems (Section 2.1). Afterwards, I will emphasize the necessity to measure political polarization in parliament (Section 2.2) and highlight the potential of using text as data for doing so (Section 2.3).

2.1 Assessing the Impact of Political Polarization on Politics

According to Easton (1965), political systems constantly perceive input from all parts of society. Likewise, this input is then converted into outputs, such as decisions or actions, which in turn affect the future demands of society towards the political system. Dealing with political polarization is no exception. Generally, researchers acknowledge that political polarization is inextricably linked to the functioning of any political system. However, when evaluating the impact of polarization on the effectiveness of the political process in modern democracies, scholars have come to an ambivalent assessments.

For the one part, moderate levels of political polarization have been acknowledged to be beneficial for democracies (Downs 1957; McCoy, Rahman, and Somer 2018; Sartori 1976, 2005). For instance, case studies from North America (Campbell 2018), Africa (LeBas 2006) and Europe (Enyedi 2016) all provide evidence that a polarized environment helps voters to correctly differentiate between political alternatives. Furthermore, it enables parties to mobilize supporters and strengthen internal cohesion. Speaking more generally, political polarization thus constitutes a basic condition for social and political progress. This process, which has been described by Mudde and Kaltwasser (2013) as “inclusionary populism” (p. 147) thus functions as a positive force for democracy by “[giving] voice to groups that do not feel represented [. . .] and [changing] the political agenda to include these marginalized voices” (p. 168).

For the other part, however, several studies provide evidence that critical levels of political polarization can seriously hamper the functioning and integrity of contemporary democratic systems (Bergmann, Bäck, and Saalfeld 2021; Maoz and Somer-Topcu 2010; Petri and Biedenkopf 2021; Sani and Sartori 1983; Sakatomo 2017). The theoretical explanation for this mechanism can be found in social identity theory introduced by Tajfel et al. (1979). In their popular paper, they sought to explain intergroup conflict with a set of explanation patterns, such as social categorization, ingroup favouritism and outgroup rejection. Hence, these patterns have been acknowledged to be especially strong when the levels of conflict between groups are high (cf. McGarty et al. (1992)). Assessing the negative impact of political polarization on democratic political systems, McCoy, Rahman, and Somer (2018) consequently argue that the negative effects of political polarization are especially severe when large parts of society can be assigned to a few mutually exclusive identities and interests. If high levels of polarization further cement cleavages between these groups, people will tend to abstain from constructive exchange and further develop stereotypes, such as feelings of someone's own superiority (Eidelson and Eidelson 2003) or the de-individualization of members of the other group (Reicher and Levine 1994). In addition to that, political polarization can also foster the spread of "exclusionary populism" (Mudde and Kaltwasser 2013, p. 147). This form of populist behavior has recently gained popularity in formerly stable democracies and has been described by scholars as power-driven, antagonistic against minority groups and generally harmful to the foundations of representative democracy (Bergmann, Bäck, and Saalfeld 2021; Caramani 2017).

Empirically, several studies have found indices of a negative impact of critical levels of political polarization on the functioning of the political system. On the individual level, the main findings constitute a negative impact on individuals willingness to contribute to public goods (Cornelson and Miloucheva 2020) and greater acceptance of growing authoritarianism (Hetherington and Weiler 2009; Somer and McCoy 2018). On the political level, high polarization is also associated with lessened coalition stability (Bergmann, Bäck, and Saalfeld 2021; Maoz and Somer-Topcu 2010), increased party fragmentation (Stroschein 2011) and inefficient policy making (Strøm, Müller, and Bergman 2008; Burns 2019; Petri and Biedenkopf 2021).

2.2 On the Necessity to Measure Political Polarization in Parliament

Considering the various positive and negative effects of political polarization on politics and society presented in the previous section, scholars have recognized the importance to systematically study the phenomenon of political polarization from an early stage on (Peterson and Spirling 2018). However, in order to develop and test theories in the social sciences, researchers always depend on valid and reliable methods to operationalize and measure latent constructs such as political polarization (cf. Popper (1963) and Reiter (2017)).

Therefore, several approaches have been developed to serve this purpose. One branch of literature, for instance, relies on census and cross-country survey data to measure individual and group-aggregated conflict. Thereby, polarization is usually operationalized through respondents self-placement on a left-right scale (DiMaggio, Evans, and Bryson 1996; Grechyna 2016; Silva 2018) or their emotional attachments towards political actors (Boxell, Gentzkow, and Shapiro 2017). Another branch of literature focuses on peoples interactions on social networks like *Twitter* or *Facebook* (Morales et al. 2015; Yardi and Boyd 2010; Kiran and Weber 2017). Here, polarization is often measured by examining user's network, their tweeting behavior and the content they share, such as posts, retweets or hashtags.

The most promising approach, however, constitutes the analysis of parliamentary data. This is because the parliamentary arena constitutes the most central part of any democratic discourse (Bayley 2004). Thereby, its topics and conflicts stand representatively for the political and social cleavages in society. Analysing the outputs of the political system thus allows scholars to justify their research by examining the most salient topics facing societies these days (Goet 2019).

On the aggregated level, one proven method constitutes to use party fragmentation as a proxy for political conflict (Tepe 2014; Corrales 2005). However, the scope for interpretation remains restricted to analysing greater trends on the macro level. This is, because party composition in parliament usually changes at a relatively slow pace and might be influenced by the political system and its election procedure too (Golosov 2015).

On the individual level, a large body of work builds on on legislative roll-call votes to assess the coherence of MP decisions (Laver, Benoit, and Garry 2003; Poole and Rosenthal 1985; Wright 2007). Tough, from a methodological point of view, these approaches suffer some important shortcomings as well. Primarily, unobserved factors like party discipline or strategic voting behaviour represent a severe constrain to the validity of these approaches (Spirling and McLean 2007). Furthermore, the direction of causality might be misinterpreted, since voting behaviour is "more a product of the political process [...] than causally prior to [its polarization process]" (Laver, Benoit, and Garry 2003, p. 311)

Due to that, a growing group of scholars have instead shifted their attention to analysing parliamentary texts and debate transcripts. The last section in this chapter will thus explain and outline the potential of measuring political polarization using textual data.

2.3 Examining the Potential of measuring Polarization using NLP

Measuring political polarization using parliamentary texts and debate transcripts has gained reasonable popularity in the last years (Abercrombie and Batista-Navarro 2020). From an academic point of view, a combination of different reasons and social and political developments have contributed to this trend.

Starting with the first reason, scholars agree that textual data represents a valuable data resource that facilitates substantially valuable inferences about political discourse. Hence, the content and topics of what members of parliament speak about in plenary is usually revolving around the core conflict lines of politics. This is particularly reflected by the fact that a parliamentary speech enables MPs to express dissent and polarized views in a more nuanced way when compared to simple roll-call votes. Therefore, analysing political speeches enables researchers to explore and measure speakers position and patterns of argumentation in a high-dimensional setting (Goet 2019). Additionally, political speeches are typically held by one MP on one specific topic. Thereby, they remain at a conceptually relevant level of analysis and can be aggregated up to any desired level, such as e. g. MPs position on a specific topic, MP sentiments towards a bill or, more generally, parliamentary polarization over a chosen period of time (Proksch et al. 2019).

Another reason for the popularity of text as data approaches is connected to the immense liberating potential for political science research. This is because the digitization and provision of parliamentary transcripts as open data has enabled scholars to easily get access to vast amounts of textual data previously hidden from research (Beelen et al. 2017). Often, several hundred speeches are being delivered by MPs in one parliamentary session alone, which results in hundreds of thousand textual data points over the year to be provided as open data. Consequently, this enables the systematic assessment of large-scale text collections without massive funding support for researchers (Grimmer and Stewart 2013) Additionally, once the data is public, it can be "analysed, reanalyzed again without becoming jaded or uncooperative [...] and others can replicate, modify, and improve the estimates involved or can produce completely new analyses using the same tools" (Laver, Benoit, and Garry 2003, p. 311). Even tough other areas of political science research have made advantages in providing data publicly as well (cf. *open science* Vicente-Sáez and Martınez-Fuentes (2018)), analysing parliamentary textual data is still one of the most promising approaches to provide easy and freely accessible data in the area of political discourse research (Hardwicke et al. 2018).

Lastly, technical and theoretical advantages in NLP methods promise a great potential for future research. As Grimmer and Stewart (2013) admits, the majority of popular NLP methods are too simplistic and methodologically unsound to make inferences about the *true* process of data generation. Nevertheless, even comparatively simplistic models can already provide researchers with highly relevant information with the textual data under study, such as filtering a high number of texts into polarization categories or placing them on an ideological scale. As Abercrombie and Batista-Navarro (2020) note this is true for the analysis of parliamentary debates where several studies have relied on NLP to improve the performance of the information retrieval process. Additionally, the future promises an even deeper understanding of language and textual data. With the ongoing rapid developments in deep learning and artificial intelligence, scholars will likely be able to further improve the semantic understanding on textual data to gain new insights into political discourse (cf. Devlin et al. (2018)).

Coming to an end, this chapter has provided an overview over the relevance of measuring political polarization using text-as-data approaches. But how should researchers actually evaluate the validity of studies performing this task, and judge the implications drawn from their research designs? In order to systematically answer this question, the next chapter will provide a structured literature reviews on all studies identified to evaluate the current state of research on measuring political polarization from textual data.

3. Literature Review: Measuring Parliament Polarization using Text-as-Data

"All quantitative models of language are wrong - but some are useful."

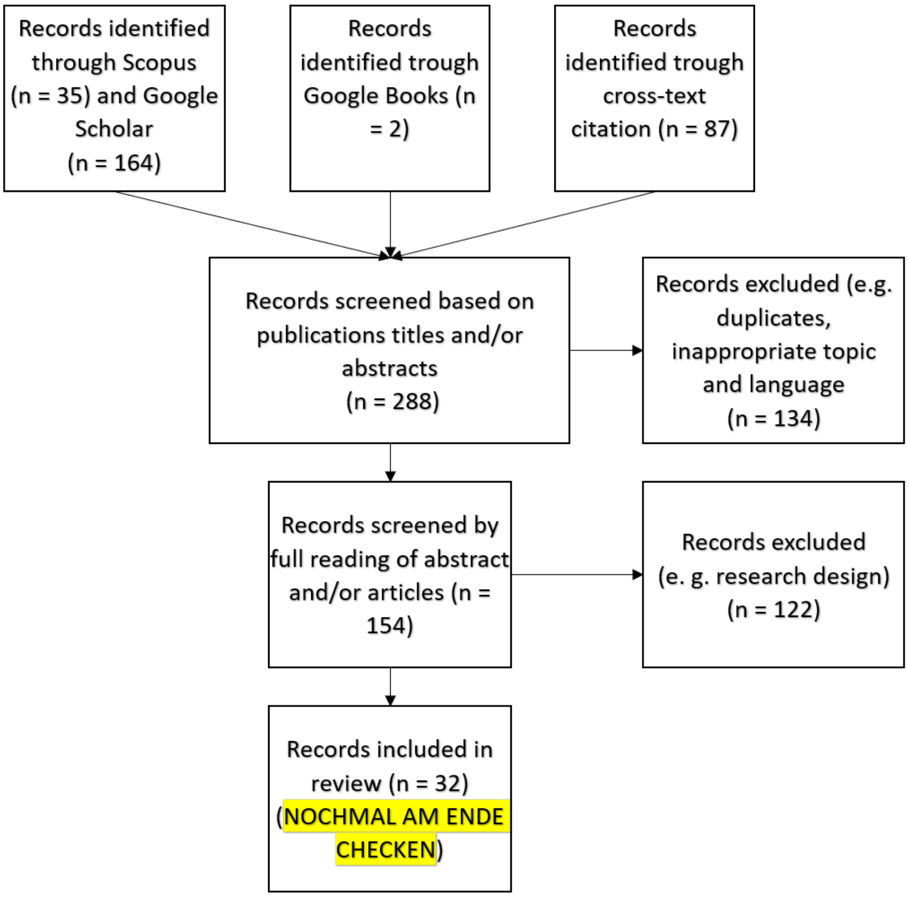
- Justin Grimmer and Brandon Stewart 2013,

In this chapter, I will first provide a short summary on the main steps in my systematic literature review (Section 3.1). Afterwards, Section 3.2 will provide the main overview over all relevant methods identified to measure parliament polarization using textual data. Lastly, I will provide a short summary and highlight similarities and differences as well as strengths and weaknesses between the methods presented (Section 3.3)

3.1 PRISMA Method

In order to demonstrate the transparency of my literature search and to ensure the completeness of the studies under review, the literature review was conducted based on a slightly simplified variant of the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines (Liberati et al. 2009). Starting with the literature search, two central literature databases (*Google Scholar* and *Scopus*) were identified, which ensure access to a whole scientific range of relevant publications. Since the search terms ["political polarization" and “parliament”] generated a very high number of search results in the databases (>17,000), it was specified in a second round using the keywords [”political polarization” AND “parliament“ AND “measurement" AND “transcripts"], which limited the preliminary literature list to 1,140 results. Using the PRISMA scheme, the preliminary literature list was further restricted with the help of a number of selection criteria. On the one hand, only texts in English or German were selected that had been published online after 1990 and were freely accessible to users of the University of Warwick. Secondly, only peer-reviewed articles were selected, and so-called "grey literature" was only included in exceptional cases (e.g. direct reference in the literature). After removing duplicates, those articles in the selected list were then sorted out by checking the title and abstract, to ensure that they applied an NLP method to measurement parliament polarization for a given study context. Lastly, in a final step, cross-referencing in the most relevant publications for this work was considered in more detail (”snowballing”, cf. Gentles et al. (2015)). This finally reduced the risk of overlooking important literature that was not found by the keywords mentioned. At the end of this selection procedure, 32 articles could be included in the final literature selection (cf. Figure 1).

Figure 1. PRISMA Statement



3.2 Approaches to Measure Parliament Polarization

3.2.1 Sentiment Lexicons

From an early stage on, several authors have relied on lexical-based methods to measure polarization in parliamentary documents (Ahmadalinezhad and Makrehchi 2018; Balahur, Kozareva, and Montoyo 2009; Biessmann 2016; Haselmayer and Jenny 2017; Liu and Lei 2018; Proksch et al. 2019; Dzieciątko 2018; Onyimadu et al. 2013). These approaches, which are also known as polarity classification, opinion mining or sentiment analysis, thus assume that higher levels of polarization reflect themselves in the use of more polarized vocabulary (Abercrombie and Batista-Navarro 2020). Thereby, these studies rely on lexicons and annotated datasets, where each word is associated with a polarity score on either a metrical (-1 to $+1$) or ordinal ("positive", "neutral", "negative") scale. After assigning the dictionary values to all of the respective words in a given document, the scores are then summarized (e. g. by taking the average) and an overall polarity score is calculated for each document (Yadollahi, Shahraki, and Zaiane 2017). In the past, several studies have applied lexical-based methods to study the polarity in parliamentary debates. Balahur, Kozareva, and Montoyo (2009), for instance, combined three different lexicon sources to evaluate both the polarity of opinion and emotions expressed from the transcripts of U.S. Congressional floor debates. By comparing their results to vote outcome of legislative bills, they are able to reach a classification accuracy of around 76 per cent on the individual speaker segments based on their computed polarity score. Likewise, Proksch et al. (2019) apply their multilingual sentiment approach on the ParlSpeech data set (cf. Rauh, Wilde, and Schwalbach (2017)) consisting of 3.9 million plenary speeches of seven European states. Their findings suggest that the calculated sentiment scores were able to capture important aspects of legislative conflict, regardless of the national background under study. Another approach is brought forward by Haselmayer and Jenny (2017). In their paper, they rely on crowdcoding to develop their own dictionary of negative and positive sentiments on a corpus of Austrian party press releases and parliamentary debates. When validating their results with the "gold standard [...] from human coding" (p. 2631) for a random sample of 200 test sentences, their dictionary ratings show a solid correlation of 0.65 with 84% coverage with the manual expert ratings.

3.2.2 Ideological Text Scaling

Another popular approach in the measurement of political polarization can be summarized under the umbrella term ideological text scaling (Baturo, Dasandi, and Mikhaylov 2017; Gentzkow, Shapiro, and Taddy 2016; Jensen et al. 2012; Kim, Londregan, and Ratkovic 2018; Laver, Benoit, and Garry 2003; Schwarz, Traber, and Benoit 2017; Spirling, Huang, and Patrick 2018; Curini, Hino, and Osaka 2020). The main theoretical concept constitutes a spatial model of politics, which has first been developed by early research in the field of party polarization and party competition (cf. Downs (1957) and Sartori (1976)). Hence, the basic idea behind this framework assumes that political parties are usually aligned along one conflict line, such as a left-right or a liberal-conservative continuum (Adams, Merrill III, and Grofman 2005). In times of elections, the party positions on this policy space are then evaluated by the voters, which will typically select the party most proximate to their own position (Dalton 2008). As Dalton (2008) notes, this theoretical concept also inherently implies "a concern for the degree of polarization in a party system" (p. 901) given by the distance between the parties and, thus, their political proximity. Hence, researchers have begun to apply this spatial concept of politics to measure political polarization in parliamentary debate transcripts (Grimmer and Stewart 2013). Doing so, they apply several methods to derive ideological positions from textual data such as parliamentary transcripts. Thereby, they resort to measure polarization by assessing the similarity between groups based on the sociological concept of intra-group homogeneity and inter-group heterogeneity (cf. Deutsch (1971)). This idea behind this concept is described by Esteban and Ray (1994) as such:

> Suppose that a population of individuals may be grouped according to some vector of characteristics into "clusters," such that each cluster is very "similar" in terms of the attributes of its members, but different clusters have members with very "dissimilar" attributes. In that case we say that the society is polarized"

In applied research, scholars have mainly built on two computer-based content analysis techniques to measure the ideological positions of speakers, namely Wordscores and Wordfish.

Wordscores

Starting with the first method mentioned, the Wordscore algorithm was first introduced by Laver, Benoit, and Garry (2003) based on a Bayesian approach. Thus, in order to apply the algorithm, scholars have to first identify a set of reference texts which are known to represent the extremes of the political space (Step 1). Then, word scores S_{wd} for a given word w on dimension d are calculated as

$$S_{wd} = \sum_{r} (P_{\text{wr}} \cdot A_{\text{rd}}) \tag{3.1}$$

Where P_{wr} is a matrix of probabilities of a word w in a reference text r and A_{rd} are the a priori reference text scores A_{rd} for a reference text r on a dimension d (Step 2). In a final step (Step 3), the positions of the actual texts S_{vd} for document v on dimension d is estimated by the "mean dimension score of all of the scored words that it contains, weighted by the frequency of the scored words" (cf. p. 316). Speaking more generally, the positioning of any document v on dimension d is thus depending on how similar the words used in document v are in relation to the reference texts r.
While Laver, Benoit, and Garry (2003) initially applied the Wordscore algorithm to party manifestos, researchers have also relied on these mechanisms to measure the parliamentary polarization. Herzog and Benoit (2015), for instance, analyze 27 Irish budget debates for the time period from 1987 to 2013 to measure the ideological divide between governing parties and coalitions. Likewise, Baturo, Dasandi, and Mikhaylov (2017) use Wordscores to position United Nations general debate speeches on a US-Russia rivalry policy dimension using statements by the US and Russia delegates as reference texts.

Wordfish

However, one important shortcoming of the Wordscores algorithm constitutes the selection of appropriate reference texts. In order to tackle this issue, Slapin and Proksch (2008) have developed the text scaling model Wordfish, which is does not require the use of reference texts. Like Wordscores, the model assumes that "the relative word usage of parties provides information about their placement in a policy space" (p. 708). However, the main difference lies in the assumption that word frequencies are drawn from a statistical Poisson distribution with:

$$\begin{aligned} y_{ijt} &\sim Poisson(\lambda_{ijt}) \\ \lambda_{ijt} &= exp(\alpha_{it} + \psi_j + \beta_j * \omega_{it}) \end{aligned} \tag{3.2}$$

where y_{ijt} is the count of word j in party i's text at time t, α_{it} is a set of document fixed effects (captures document lengths), Ψ_j is a set of word fixed effects (captures average word frequency), β_j is an estimate of a word specific weight capturing the importance of the word j in discriminating between parties, and ω_{it} is the estimate of party i's position in the year t (p. 709). Applying the Wordfish model to parliamentary debates, the model is thus not only able to estimate the ideological position of MP speeches ω_{it} based on the shared word usage across all texts, but is also able to recover which words have more explanatory power to differentiate across political speeches as given by the word weight β_j (cf. Curini, Hino, and Osaka (2020)).

Being able to apply this unsupervised technique for ideological scaling, several authors have relied on Wordfish to linearly order parties and politicians across political dimensions. Lowe and Benoit (2013), for instance, focus on validating the model estimates on a austerity debate in the Irish parliament in 2009 against the systematic ranking of around twenty human readers. Running their analysis, they find a "high degree of correspondence" between the models estimates and human judgment, even tough they claim that some assumptions of the statistical model are violated (p. 312). Examining asylum debates in the European parliament, Frid-Nielsen (2018) furthermore analyse 876 speeches from held between 2004 and 2014. Developing their own *Wordshoal* model, Lauderdale and Herzog (2016) apply a two-step approach by adding Bayesian factor analysis on the *Wordfish* debate specific estimate ω_{it} to aggregate them into one general latent position for each legislator. Moreover, previous mentioned studies like Proksch et al. (2019) and Goet (2019) rely on Wordfish as well to cross-validate other techniques in the analysis of parliamentary conflict.

3.2.3 Machine Learning Classification Accuracy

As a last method, the literature review also identified a third branch of literature to measure parliament polarization, namely the classification accuracy of a machine learning (ML) algorithm (Peterson and Spirling 2018; Frech, Goet, and Hug 2018; Søyland 2020; Goet 2019; Idelberger 2020) (GENTZKOW 2019 NOCH EINFÜGEN). This approach has been introduced by Peterson and Spirling (2018) and has gained considerable academic attention in the academic area since then. Similar to the ideological scaling methods, this approach is based on a measure of similarity between texts. However, the computation of polarization scores at the document level follows a different approach. As Peterson and Spirling (2018) explain:

> "How distinguishable [MPs] are in practice is determined by a set of machine learning algorithms. Put very crudely, after being trained on a portion of the speeches, the models are then required to predict the most likely 'label'—that is, party identity [...] When the machine learning accuracy—in the technical sense—is low [..] we deduce then that we are in a world of relatively low polarization. By contrast, when accuracy is high, and the machine does well at discriminating between partisans based on their utterances, [...] we are in a more polarized era." (p. 2-3).

They illustrate their method by applying four different ML algorithms to measure varying levels of UK parliament polarization between 1935 and 2013. By validating their approach with qualitative and quantitative historical records, they claim that their estimates are able to trace back major trends in parliament polarization. Others have come to similar conclusions. Goet (2019), for instance, compares the results of an ideological scaling algorithm and an ML classifier based on an validation framework. He finds that the latter, which "incorporates information about party affiliation [...], show a high degree of face-, construct-, and convergent validity." (p. 535). Likewise, Søyland (2020) analyses Norwegian parliament speeches using a stochastic gradient boost (SGB) classifier. However, he takes a more critical standpoint by emphasizing the sensitivity to prepossessing decisions, which severely affected the stability of his estimates. Furthermore, he criticizes the failure to observe omitted variables, such as institutional attributes or MP specific variables (p. 25). Most recently, other scholars have started to apply non-linear neural networks as well. Abercrombie and Batista-Navarro (2018), for instance, rely on a Multi-layered Perception (MLP) neural network to classify data from the *Hansard* corpus of UK parliamentary debate transcripts with government vs. opposition labels.

Table 3.1 gives an overview over all studies covered in this literature review.

Table 3.1. *Overview Systematic Literature Review*

Method	Submethod	Relevant studies
Sentiment Analysis	Dictionary	Ahmadalinezhad and Makrehchi 2018; Balahur, Kozareva,and Montoyo 2009; Biessmann 2016; Haselmayer and Jenny 2017; Liu and Lei 2018; Proksch et al. 2019; Dzieciatko 2018; Onyimadu et al. 2013
Ideological Scaling	Wordscores	Laver, Benoit, and Garry 2003; Herzog and Benoit 2015; Baturo, Dasandi, and Mikhaylov 2017;
	Wordfish	Slaping and Proksch 2008; Lowe and Benoit 2013; Lauderdale and Herzog 2016; Schwarz, Traber, and Benoit 2017; Frid-Nielsen 2018; Kim, Londregan, and Ratkovic 2018; Goet 2019; Curini,Hino, and Osaka 2020
	Others	Spirling, Huang, and Patrick 2018; Jensen et al. 2012; Gentzkow,Shapiro, and Taddy 2016
ML Accuracy	Linear	Peterson and Spirling 2018; Goet 2019; Idelberger 2020; Søyland 2020
	Non-Linear	Abercrombie and Batista-Navarro (2018)

3.3 Evaluation and Comparison

As presented in the previous section, several methods have been applied to measure political polarization in parliament speech data. However, as Grimmer and Stewart (2013) explain, all

methodological characteristics might question the validity of the methods under study. Starting again with the However, *lexical-based methods* are not without shortcomings. Even though researchers can implement them easily and resource-efficient to big corpses of textual data, their simplicity prevents them from detecting different semantic meanings of words in different contexts. Rheault et al. (2016) illustrate this point with the word “health”, which is generally considered to bear a positive sentiment. In the context of political debates, however, the word health also often relates to formal definitions, such as e. g. a countries “Ministry of Health”, which bears a more descriptive and neutral sentiment. On top of that, the bag-of-word approach (cf. Harris (1954) and Zhang, Jin, and Zhou (2010) completely ignores grammar, sentence structure as well as word order altogether and, thus, is only able to provide a relatively simple tool in the analysis of textual data.

Another approach

Table 3.2. *Comparing Mehods to measure political polarization*

Method	Reference Point	Computation	Shortcomings	
Sentiment Lexicons	Word Sentiment	Lexicons)	absolut	unsupervised
Ideological Scaling	Intervene to provide reinforcement	Sangaris (CAR)		
Machine Learning	Stand by or prepare to intervene	Licorne (Côte d'Ivoire)		

4. Research Design

In this chapter, I present all relevant steps in preparing my research design. I begin with describing the process of case selection (Section 4.1). Subsequently, I will introduce all approaches to measure polarization in my analysis (Section 2.2). Ultimately, I discuss my performance metrics and present approaches to validate the consistency of all methods presented (Section 4.3).

4.1 Case Selection and Data

4.1.1 German Politics and the Covid-19 Pandemic

In order to select an appropriate sample of parliamentary textual data, I follow the recommendations of Slapin and Proksch (2008) and restrict my data sample to one specific policy dimension (cf. section 3.3). For this study, I define my main debate topic centered around discussions dealing with the epidemic control of the Covid-19 pandemic in Germany. Generally, Germany experienced similar similar pandemic progressions as the other European countries. Between March and May, the first wave of the pandemic reached its peak, leading to school closures, strict contact restrictions and curfews imposed by the federal government from 22 March on (Bosen 2021)[1]. After a decline of infection rates and increased public pressure in May 2020, Germany experienced relatively low infection rates and an relaxation of government regulations throughout the summer months. In the autumn, however, the second wave of the pandemic emerged, which ultimately lead again to curfews and strict contact restrictions lasting throughout the winter until April 2021 (Bosen 2021). Figure 1 in the Appendix provides an overview over the daily infection cases.

While the Covid-19 pandemic had an highly disruptive impact on German society, one should also expect the levels of political polarization varying throughout the course of pandemic. First results examining the course of the pandemic support this claim (Balmford et al. 2020; Louwerse et al. 2021; Juhl et al. 2021). Most prominent, a recent study by Louwerse et al. (2021) examines the degree of German parliament polarization from members of the opposition parties between February and July 2020. Their findings suggest a parabolic progression, with more negative sentiments expressed towards the government at the beginning and the end of their reference period, and more positive sentiments on the peak of the first wave in March and April 2020. These findings are consistent with the "rally around the flag" literature, which argues that, in times of crises, public support for governments usually increases and opposition parties position themselves close to the government side (Chowanietz 2011; Lee 1977). Likewise, Naumann et al. (2020) observe

1. From a legal perspective, decisions were primary coordinated between the federal and state level. Except for issues of border affairs, the federal government usually issued formal guidelines based on the German Infection Protection Act (IfSG) (*Infektionsschutzgesetz*). These guidelines were then implemented into legally binding regulations by the state governments, cf. Saurer (2020)

increased levels of political contestation in German politics once the infection rates started to decrease in May 2020 as well. Even tough their study mainly focuses on public reactions towards the first lockdown, their findings also provide evidence that the issues surrounding epidemic containment policies are a highly emotional issue and, thus, will likely lead to varying levels of political polarization on the level of society and politics.

4.1.2 Data Collection

In order to test my hypotheses and compare the predictions of the NLP techniques identified, I rely on an individually composed dataset of speech transcripts from the German parliament (*Bundestag*). The dataset was collected via a gradual approach combining different publicly available data sources. As a starting point, I first access the extensive dataset provided by the non-profit project "Open Discourse" covering 899.526 individual speeches and statements in the time period between 1949 and 2020 (Richter et al. 2020). While the administration of the *Bundestag* provides parliamentary protocols only in (non-machine readable) PDF and XML format, Open Discourse provides a fully scraped database of every parliamentary speeches held in the *Bundestag* together with some metadata, such as speaker characteristics or a direct link to the PDF protocol from the Bundestag Website.[2] In a first round, I limited the dataset to only speeches delivered by MPs and removed all statements from government officials or external guests. Furthermore, I restricted the time period to speeches held between January 1, 2020 and December 17, 2020. Given that the COVID-19 pandemic has been spreading from Wuhan, China since December 2019 ((WHO) 2020), public officials in Germany have been discussing preventive measures throughout January, even before the first confirmed infection on January 27, 2020 (Rothe et al. 2020).

However, in order to restrict the sample to only debates covering the handling of the Covid-19 pandemic, I need to draw additional information from the *Documentation and Information System for Parliamentary Materials of the German Bundestag* (DIP) (Bundestag 2021). On their website, the DIP provides advanced search option to filter all operations, documents and activities within the *Bundestag* and the *Bundesrat* representing the sixteen federated states. Using these filters, I thus restricted my search results to only individual speeches with the keywords ["Covid-19" and "Seuchenbekämpfung"] held between January 01, 2020 and December 31, 2020 present in the Bundestag plenary records. Ultimately, this restricted my search query to 667 individual speeches meeting these conditions. In a second step, these search results were then exported as a word-document and scraped into tabular format.[3]. In a final step, I merged both data sets on the variables *Date of Speech*, *MP Last Name* and *MP Party*, thus keeping only these speeches in the dataset also present in the DIP selection. In XXX cases, a member of parliament would speaker more than one time per session, providing the algorithm with more than one unique option. In these cases, I rely on an manual approach and personally assign the correct speech to entry in the DIP reference data set. Ultimately, a total of 617 speeches from 25 debates were selected for further analysis. Table 7.1 in the Appendix provides an overview over all debates identified.

2. In order to access the dataset, please visit the documentation of the project at: https://open-discourse.github.io/open-discourse-documentation/1.0.0/index.html

3. For a detailed description, please visit the Code at the authors Github Profile online retrievable at: https://github.com/lukasbirki/Thesis

4.2 Measurement

In line with authors such as Main Dimension: Government-Opposition Polarization

4.2.1 Sentiment Approach

4.2.2 Ideological Scaling Approach

4.2.3 Classification Accuracy Approach

4.3 Validation

4.3.1 Validation Scheme

4.3.2 Qualitative Comparison

5. Results

5.0.1 Descriptive Statistics

5.0.2 Validation

6. Discussion

6.1 Limitations

7. Conclusion

Bibliography

(WHO), World Health Organization. 2020. *Coronavirus disease 2019 (covid-19),* April. https://www.who.int/docs/default-source/coronaviruse/situation-reports/20200423-sitrep-94-covid-19.pdf?sfvrsn=b8304bf0_4#:~:text=The%20first%20human%20cases%20of,%2C%20some%20did%20not..

Abercrombie, Gavin, and Riza Batista-Navarro. 2018. 'aye'or 'no'? speech-level sentiment analysis of hansard uk parliamentary debate transcripts. In *'aye'or 'no'? speech-level sentiment analysis of hansard uk parliamentary debate transcripts.*

———. 2020. Sentiment and position-taking analysis of parliamentary debates: a systematic literature review. *Journal of Computational Social Science,* 1–26. ISSN: 2432-2725.

Adams, James F., Samuel Merrill III, and Bernard Grofman. 2005. *A unified theory of party competition: a cross-national analysis integrating spatial and behavioral factors.* Cambridge University Press. ISBN: 113944400X.

Ahmadalinezhad, Mahboubeh, and Masoud Makrehchi. 2018. Detecting agreement and disagreement in political debates. In *Social, cultural, and behavioral modeling,* edited by Robert Thomson, Christopher Dancy, Ayaz Hyder, and Halil Bisgin, pp. 54–60. Cham: Springer International Publishing. ISBN: 978-3-319-93372-6.

Balahur, Alexandra, Zornitsa Kozareva, and Andrés Montoyo. 2009. Determining the polarity and source of opinions expressed in political debates. In *Computational linguistics and intelligent text processing,* edited by Alexander Gelbukh, pp. 468–480. Berlin, Heidelberg: Springer Berlin Heidelberg. ISBN: 978-3-642-00382-0.

Balmford, Ben, James D Annan, Julia C Hargreaves, Marina Altoè, and Ian J Bateman. 2020. Cross-country comparisons of covid-19: policy, politics and the price of life. *Environmental and Resource Economics* 76 (4): 525–551.

Baturo, Alexander, Niheer Dasandi, and Slava J. Mikhaylov. 2017. Understanding state preferences with text as data: introducing the un general debate corpus. *Research & Politics* 4 (2): 2053168017712821. ISSN: 2053-1680.

Bayley, Paul. 2004. *Cross-cultural perspectives on parliamentary discourse.* Vol. 10. John Benjamins Publishing.

Beelen, Kaspar, Timothy Alberdingk Thijm, Christopher Cochrane, Kees Halvemaan, Graeme Hirst, Michael Kimmins, Sander Lijbrink, Maarten Marx, Nona Naderi, and Ludovic Rheault. 2017. Digitization of the canadian parliamentary debates. *Canadian Journal of Political Science/Revue canadienne de science politique* 50 (3): 849–864. ISSN: 0008-4239.

Bergmann, Henning, Hanna Bäck, and Thomas Saalfeld. 2021. Party-system polarisation, legislative institutions and cabinet survival in 28 parliamentary democracies, 1945–2019. *West European Politics,* 1–19. ISSN: 0140-2382.

Biessmann, Felix. 2016. Automating political bias prediction. *arXiv preprint arXiv:1608.02195.*

Bosen, Jens, Ralf; Thurau. 2021. Chronology: how covid has spread in germany. Accessed June 28, 2020. https://www.dw.com/en/chronology-how-covid-has-spread-in-germany/a-58026877.

Boxell, Levi, Matthew Gentzkow, and Jesse M. Shapiro. 2017. Greater internet use is not associated with faster growth in political polarization among us demographic groups. *Proceedings of the National Academy of Sciences* 114 (40): 10612–10617. ISSN: 0027-8424.

Bundestag, German. 2021. *Documentation and information system for parliamentary materials of the german bundestag,* July. https://dip.bundestag.de/erweiterte-suche?f.wahlperiode=19&rows=25.

Burns, Charlotte. 2019. In the eye of the storm? the european parliament, the environment and the eu's crises. *Journal of European Integration* 41 (3): 311–327. ISSN: 0703-6337.

Campbell, James E. 2018. *Polarized: making sense of a divided america.* Princeton University Press. ISBN: 0691180865.

Caramani, Daniele. 2017. Will vs. reason: the populist and technocratic forms of political representation and their critique to party government. *American political science review* 111 (1): 54. ISSN: 0003-0554.

Chowanietz, Christophe. 2011. Rallying around the flag or railing against the government? political parties' reactions to terrorist acts. *Party Politics* 17 (5): 673–698.

Cornelson, Kirsten, and Boriana Miloucheva. 2020. *Political polarization, social fragmentation, and cooperation during a pandemic.* University of Toronto, Department of Economics.

Corrales, Javier. 2005. In search of a theory of polarization: lessons from venezuela, 1999-2005. *European Review of Latin American and Caribbean Studies/Revista Europea de Estudios Latinoamericanos y del Caribe,* no. 79, 105–118.

Curini, Luigi, Airo Hino, and Atsushi Osaka. 2020. The intensity of government–opposition divide as measured through legislative speeches and what we can learn from it: analyses of japanese parliamentary debates, 1953–2013. *Government and Opposition* 55 (2): 184–201. ISSN: 0017-257X.

Dalton, Russell J. 2008. The quantity and the quality of party systems: party system polarization, its measurement, and its consequences. *Comparative Political Studies* 41 (7): 899–920. ISSN: 0010-4140.

Deutsch, Morton. 1971. Conflict and its resolution. *Conflict Resolution: Contributions of the Behavioral Sciences.*

Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. Bert: pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805.*

DiMaggio, Paul, John Evans, and Bethany Bryson. 1996. Have american's social attitudes become more polarized? *American journal of Sociology* 102 (3): 690–755. ISSN: 0002-9602.

Downs, Anthony. 1957. An economic theory of democracy.

Dzieciątko, Mariusz. 2018. Application of text analytics to analyze emotions in the speeches, edited by International Conference on Information Technologies in Biomedicine. Springer.

Easton, David. 1965. A framework for political analysis. *Englewood Cliffs, HJ: Prentice-Hall.*

Eidelson, Roy J., and Judy I. Eidelson. 2003. Dangerous ideas: five beliefs that propel groups toward conflict. *American psychologist* 58 (3): 182. ISSN: 1935-990X.

Enyedi, Zsolt. 2016. Populist polarization and party system institutionalization: the role of party politics in de-democratization. *Problems of Post-communism* 63 (4): 210–220. ISSN: 1075-8216.

Esteban, Joan-Maria, and Debraj Ray. 1994. On the measurement of polarization. *Econometrica: Journal of the Econometric Society,* 819–851. ISSN: 0012-9682.

Frech, Elena, Niels D. Goet, and Simon Hug. 2018. Shirking and slacking in parliament. *Legislative Studies Quarterly,* ISSN: 0362-9805.

Frid-Nielsen, Snorre Sylvester. 2018. Human rights or security? positions on asylum in european parliament speeches. *European union politics* 19 (2): 344–362. ISSN: 1465-1165.

Galston, William A. 2018. The populist challenge to liberal democracy. *Journal of Democracy* 29 (2): 5–19. ISSN: 1086-3214.

Gentles, Stephen J., Cathy Charles, Jenny Ploeg, and K. Ann McKibbon. 2015. Sampling in qualitative research: insights from an overview of the methods literature. *The qualitative report* 20 (11): 1772–1789. ISSN: 1052-0147.

Gentzkow, Matthew, Jesse M. Shapiro, and Matt Taddy. 2016. *Measuring polarization in high-dimensional data: method and application to congressional speech.* National Bureau of Economic Research.

Goet, Niels D. 2019. Measuring polarization with text analysis: evidence from the uk house of commons, 1811–2015. *Political analysis* 27 (4). ISSN: 1047-1987.

Goldberg, Andreas C., Erika J. van Elsas, and Claes H. de Vreese. 2020. Mismatch? comparing elite and citizen polarisation on eu issues across four countries. *Journal of European Public Policy* 27 (2): 310–328. ISSN: 1350-1763.

Golosov, Grigorii V. 2015. Factors of party system fragmentation: a cross-national study. *Australian journal of political science* 50 (1): 42–60.

Grechyna, Daryna. 2016. On the determinants of political polarization. *Economics Letters* 144:10–14. ISSN: 0165-1765.

Grimmer, Justin, and Brandon M. Stewart. 2013. Text as data: the promise and pitfalls of automatic content analysis methods for political texts. *Political analysis* 21 (3): 267–297. ISSN: 1047-1987.

Hardwicke, Tom E, Maya B Mathur, Kyle MacDonald, Gustav Nilsonne, George C Banks, Mallory C Kidwell, Alicia Hofelich Mohr, Elizabeth Clayton, Erica J Yoon, Michael Henry Tessler, et al. 2018. Data availability, reusability, and analytic reproducibility: evaluating the impact of a mandatory open data policy at the journal cognition. *Royal Society open science* 5 (8): 180448.

Harris, Zellig S. 1954. Distributional structure. *Word* 10 (2-3): 146–162. ISSN: 0043-7956.

Haselmayer, Martin, and Marcelo Jenny. 2017. Sentiment analysis of political communication: combining a dictionary approach with crowdcoding. *Quality & Quantity* 51 (6): 2623–2646. ISSN: 1573-7845.

Herzog, Alexander, and Kenneth Benoit. 2015. The most unkindest cuts: speaker selection and expressed government dissent during economic crisis. *The Journal of politics* 77 (4): 1157–1175. ISSN: 0022-3816.

Hetherington, Marc J., and Jonathan D. Weiler. 2009. *Authoritarianism and polarization in american politics.* Cambridge University Press. ISBN: 0521884330.

Idelberger, Felix. 2020. Do the populists have a say? estimating their effect on topic prevalence and polarization in german state legislature.

Jensen, Jacob, Suresh Naidu, Ethan Kaplan, Laurence Wilse-Samson, David Gergen, Michael Zuckerman, and Arthur Spirling. 2012. Political polarization and the dynamics of political language: evidence from 130 years of partisan speech [with comments and discussion]. *Brookings Papers on Economic Activity,* 1–81. ISSN: 0007-2303.

Juhl, Sebastian, Roni Lehrer, Annelies G Blom, Alexander Wenz, Tobias Rettig, Ulrich Krieger, Marina Fikel, Carina Cornesse, Elias Naumann, Katja Möhring, et al. 2021. Preferences for centralized decision-making in times of crisis: the covid-19 pandemic in germany.

Kim, In Song, John Londregan, and Marc Ratkovic. 2018. Estimating spatial preferences from votes and text. *Political analysis,* ISSN: 1047-1987.

Kiran, Garimella, and Ingmar Weber, eds. 2017. *A long-term analysis of polarization on twitter.* Vol. 1. ISBN: 2334-0770.

Lauderdale, Benjamin E., and Alexander Herzog. 2016. Measuring political positions from legislative speech. *Political analysis,* 374–394. ISSN: 1047-1987.

Laver, Michael, Kenneth Benoit, and John Garry. 2003. Extracting policy positions from political texts using words as data. *American political science review,* 311–331. ISSN: 0003-0554.

LeBas, Adrienne. 2006. Polarization as craft: party formation and state violence in zimbabwe. *Comparative Politics,* 419–438. ISSN: 0010-4159.

Lee, Jong R. 1977. Rallying around the flag: foreign policy events and presidential popularity. *Presidential Studies Quarterly* 7 (4): 252–256.

Liberati, Alessandro, Douglas G. Altman, Jennifer Tetzlaff, Cynthia Mulrow, Peter C. Gøtzsche, John P. A. Ioannidis, Mike Clarke, Philip J. Devereaux, Jos Kleijnen, and David Moher. 2009. The prisma statement for reporting systematic reviews and meta-analyses of studies that evaluate health care interventions: explanation and elaboration. *Journal of clinical epidemiology* 62 (10): e1–e34. ISSN: 0895-4356.

Liu, Dilin, and Lei Lei. 2018. The appeal to political sentiment: an analysis of donald trump's and hillary clinton's speech themes and discourse strategies in the 2016 us presidential election. *Discourse, Context & Media* 25:143–152. ISSN: 2211-6958.

Louwerse, Tom, Ulrich Sieberer, Or Tuttnauer, and Rudy B Andeweg. 2021. Opposition in times of crisis: covid-19 in parliamentary debates. *West European Politics,* 1–27.

Lowe, Will, and Kenneth Benoit. 2013. Validating estimates of latent traits from textual data using human judgment as a benchmark. *Political analysis* 21 (3): 298–313. ISSN: 1047-1987.

Maoz, Zeev, and Zeynep Somer-Topcu. 2010. Political polarization and cabinet stability in multiparty systems: a social networks analysis of european parliaments, 1945-98. *British Journal of Political Science,* 805–833. ISSN: 0007-1234.

McCoy, Jennifer, Tahmina Rahman, and Murat Somer. 2018. Polarization and the global crisis of democracy: common patterns, dynamics, and pernicious consequences for democratic polities. *American Behavioral Scientist* 62 (1): 16–42. ISSN: 0002-7642.

McGarty, Craig, John C. Turner, Michael A. Hogg, Barbara David, and Margaret S. Wetherell. 1992. Group polarization as conformity to the prototypical group member. *British journal of social psychology* 31 (1): 1–19. ISSN: 0144-6665.

Morales, Alfredo Jose, Javier Borondo, Juan Carlos Losada, and Rosa M. Benito. 2015. Measuring political polarization: twitter shows the two sides of venezuela. *Chaos: An Interdisciplinary Journal of Nonlinear Science* 25 (3): 033114. ISSN: 1054-1500.

Mudde, Cas, and Cristóbal Rovira Kaltwasser. 2013. Exclusionary vs. inclusionary populism: comparing contemporary europe and latin america. *Government and Opposition* 48 (2): 147–174. ISSN: 0017-257X.

Naumann, Elias, Katja Möhring, Maximiliane Reifenscheid, Alexander Wenz, Tobias Rettig, Roni Lehrer, Ulrich Krieger, Sebastian Juhl, Sabine Friedel, Marina Fikel, et al. 2020. Covid-19 policies in germany and their social, political, and psychological consequences. *European Policy Analysis* 6 (2): 191–202.

Onyimadu, Obinna, Keiichi Nakata1, Tony Wilson, David Macken, and Kecheng Liu. 2013. Towards sentiment analysis on parliamentary debates in hansard, edited by Joint international semantic technology conference. Cham.

Peterson, Andrew, and Arthur Spirling. 2018. Classification accuracy as a substantive quantity of interest: measuring polarization in westminster systems. *Political analysis* 26 (1): 120–128. ISSN: 1047-1987.

Petri, Franziska, and Katja Biedenkopf. 2021. Weathering growing polarization? the european parliament and eu foreign climate policy ambitions. *Journal of European Public Policy,* 1–19. ISSN: 1350-1763.

Pew Research Center. 2019. Public highly critical of state of political discourse in the us.

Poole, Keith T., and Howard Rosenthal. 1985. A spatial model for legislative roll call analysis. *American Journal of Political Science,* 357–384. ISSN: 0092-5853.

Popper, Karl R. 1963. Science as falsification. *Conjectures and refutations* 1 (1963): 33–39.

Proksch, Sven–Oliver, Will Lowe, Jens Wäckerle, and Stuart Soroka. 2019. Multilingual sentiment analysis: a new approach to measuring conflict in legislative speeches. *Legislative Studies Quarterly* 44 (1): 97–131. ISSN: 0362-9805.

Rauh, Christian, Pieter de Wilde, and Jan Schwalbach. 2017. The parlspeech data set: annotated full-text vectors of 3.9 million plenary speeches in the key legislative chambers of seven european states.

Reicher, Stephen, and Mark Levine. 1994. Deindividuation, power relations between groups and the expression of social identity: the effects of visibility to the out–group. *British journal of social psychology* 33 (2): 145–163. ISSN: 0144-6665.

Reiter, Bernd. 2017. Theory and methodology of exploratory social science research.

Rheault, Ludovic, Kaspar Beelen, Christopher Cochrane, and Graeme Hirst. 2016. Measuring emotion in parliamentary debates with automated textual analysis. *PloS one* 11 (12): e0168843. ISSN: 1932-6203.

Rothe, Camilla, Mirjam Schunk, Peter Sothmann, Gisela Bretzel, Guenter Froeschl, Claudia Wallrauch, Thorbjörn Zimmer, Verena Thiel, Christian Janke, Wolfgang Guggemos, et al. 2020. Transmission of 2019-ncov infection from an asymptomatic contact in germany. *New England journal of medicine* 382 (10): 970–971.

Sakatomo, ed. 2017. *Cross-national measurement of polarization in political discourse: analyzing floor debate in the us the japanese legislatures.* IEEE. ISBN: 1538627159.

Sani, Giacomo, and Giovanni Sartori. 1983. Polarization, fragmentation and competition in western democracies. *Western European party systems,* 307–340.

Sartori, Giovanni. 1976. *Parties and party systems: volume 1: a framework for analysis.* CUP Archive. ISBN: 0521291062.

———. 2005. *Parties and party systems: a framework for analysis.* ECPR press. ISBN: 0954796616.

Saurer, Johannes. 2020. Covid-19 and cooperative administrative federalism in germany. *The Regulatory Review.*

Schwarz, Daniel, Denise Traber, and Kenneth Benoit. 2017. Estimating intra-party preferences: comparing speeches to votes. *Political Science Research and Methods* 5 (2): 379–396. ISSN: 2049-8470.

Silva, Bruno Castanho. 2018. Populist radical right parties and mass polarization in the netherlands. *European Political Science Review: EPSR* 10 (2): 219. ISSN: 1755-7739.

Slapin, Jonathan B., and Sven–Oliver Proksch. 2008. A scaling model for estimating time–series party positions from texts. *American Journal of Political Science* 52 (3): 705–722. ISSN: 0092-5853.

Somer, Murat, and Jennifer McCoy. 2018. *Déjà vu? polarization and endangered democracies in the 21st century.*

Søyland, Martin. 2020. Multi-party classification of parliamentary debates: intra-party cohesion and inter-party relations measured in text.

Spirling, Arthur, Leslie Huang, and Perry Patrick. 2018. Boring in a new way: estimation and inference for political style at westminster, 1935–2018. *Available at SSRN 3235506.*

Spirling, Arthur, and Iain McLean. 2007. Uk oc ok? interpreting optimal classification scores for the uk house of commons. *Political Analysis,* 85–96.

Strøm, Kaare, Wolfgang C. Müller, and Torbjörn Bergman. 2008. *Cabinets and coalition bargaining: the democractic life cycle in western europe.* Oxford University Press.

Stroschein, Sherrill. 2011. Demography in ethnic party fragmentation: hungarian local voting in romania. *Party Politics* 17 (2): 189–204. ISSN: 1354-0688.

Tajfel, Henri, John C. Turner, William G. Austin, and Stephen Worchel. 1979. An integrative theory of intergroup conflict. *Organizational identity: A reader* 56 (65): 9780203505984–16.

Tepe, Sultan. 2014. The perils of polarization and religious parties: the democratic challenges of political fragmentation in israel and turkey. In *Religiously oriented parties and democratization,* 43–68. Routledge.

V-Dem Institute. 2019. Polarization in europe. https://www.v-dem.net/en/news/polarization-europe/.

Vicente-Sáez, Rubén, and Clara Martınez-Fuentes. 2018. Open science now: a systematic literature review for an integrated definition. *Journal of business research* 88:428–436.

Wright, Gerald C. 2007. Do term limits affect legislative roll call voting? representation, polarization, and participation. *State Politics & Policy Quarterly* 7 (3): 256–280. ISSN: 1532-4400.

Yadollahi, Ali, Ameneh Gholipour Shahraki, and Osmar R. Zaiane. 2017. Current state of text sentiment analysis from opinion to emotion mining. *ACM Computing Surveys (CSUR)* 50 (2): 1–33. ISSN: 0360-0300.

Yardi, Sarita, and Danah Boyd. 2010. Dynamic debates: an analysis of group polarization over time on twitter. *Bulletin of science, technology & society* 30 (5): 316–327. ISSN: 0270-4676.

Zhang, Yin, Rong Jin, and Zhi-Hua Zhou. 2010. Understanding bag-of-words model: a statistical framework. *International Journal of Machine Learning and Cybernetics* 1 (1-4): 43–52. ISSN: 1868-8071.

Appendix

Figure 1. Daily Covid-19 Cases in Germany
Source: https://www.worldometers.info/coronavirus/country/germany/

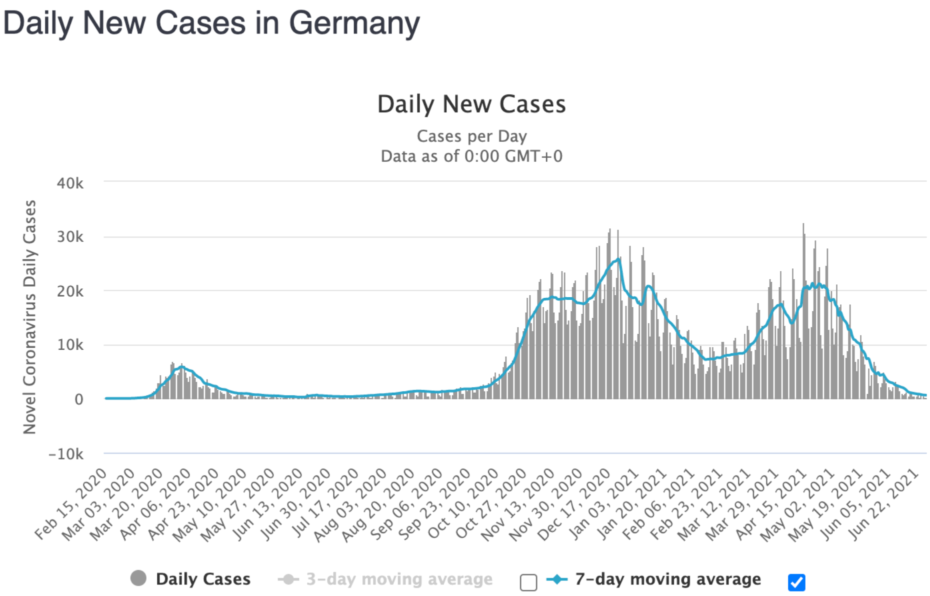


Table 7.1. *Overview Parliamentary Sessions*

No Session	Date	1 Name
1	2020-02-12	Topical Debate (Aktuelle Stunde): Prevention strategy for the coronavirus in Germany
2	2020-03-04	Government declaration (Regierungserklärung) delivered by Minister of Health Jens Spahn: Combatting the coronavirus SARS-CoV-2) in Germany
3	2020-03-25	Agreed debate (Vereinbarte Debatte): Handling of the corona crisis
4	2020-04-22	155.00
5	2020-04-23	Government declaration (Regierungserklärung) delivered by Chancellor Angela Merkel: Handling of the corona crisis in Germany and Europe
6	2020-05-06	157.00
7	2020-05-07	158.00
8	2020-05-14	160.00
9	2020-05-15	161.00
10	2020-05-27	Topical debate (Aktuelle Stunde): Supporting economic recovery after the corona crisis on all levels of the state
11	2020-05-28	163.00
12	2020-05-29	164.00
13	2020-06-18	166.00
14	2020-06-19	167.00
15	2020-07-02	170.00
16	2020-09-10	173.00
17	2020-09-17	176.00
18	2020-10-29	186.00
19	2020-10-30	187.00
20	2020-11-06	190.00
21	2020-11-18	191.00
22	2020-11-19	192.00
23	2020-11-26	195.00
24	2020-12-16	201.00
25	2020-12-17	202.00

Figure 1. Descriptive Statistics Bundestag Session (N = 25)