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The German Coal Debate on Twitter: Reactions to a Corporate Policy Process

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Abstract

Phasing out coal is a prerequisite to achieving the Paris climate mitigation targets. In 2018, the German government established a multi-stakeholder commission with the mandate to negotiate a plan for the national coal phase-out, fueling a continued public debate over the future of coal. This study analyzes the German coal debate on Twitter before, during, and after the session of the so-called Coal Commission, over a period of three years. In particular, we investigate whether and how the work of the commission translated into shared perceptions and sentiments in the public debate on Twitter. We find that the sentiment of the German coal debate on Twitter becomes increasingly negative over time. In addition, the sentiment becomes more polarized over time due to an increase in the use of more negative and positive language. The analysis of retweet networks shows no increase in interactions between communities over time. These findings suggest that the Coal Commission did not further consensus in the coal debate on Twitter. While the debate on social media only represents a section of the national debate, it provides insights for policy-makers to evaluate the interaction of multi-stakeholder commissions and public debates.

Keywords: coal phase-out, social media, Twitter, public opinion, polarization

1 Introduction

In response to current and projected severe detrimental impacts of climate change on ecosystems and livelihoods (Ranasinghe et al., 2021; Callaghan et al., 2021), governments around the world enact policies aimed at reducing greenhouse gas emissions. In line with the global ambition to limit the increase in global mean temperature to well below 2 °C as established in the Paris Agreement, all countries must achieve a rapid decarbonisation of all sectors by the middle of this century (Schleussner et al., 2016; Rogelj et al., 2018). Being the most carbon-intensive fossil fuel, coal combustion contributes about 40% to today's carbon dioxide emissions (Friedlingstein et al., 2022). Existing and planned coal infrastructure alone – if used until the end of their projected lifetime – would pose a serious threat to reaching the Paris goals (Edenhofer et al., 2018) and current and planned fossil fuel infrastructure as a whole would already exceed the remaining carbon budget for limiting warming to 1.5°C (Tong et al., 2019). But there are alternatives: Renewable energy technologies can replace coal-fired power plants and are readily available. Of many climate policy options, a coal phase-out is therefore one of the cheapest and most effective mitigation measures (Diluiso et al., 2021).

In addition to carbon dioxide emissions, coal combustion has strong impacts on the local environment. Airborne pollutants have a negative effect on ecosystems and on public health (Rauner et al., 2020a; Rauner et al., 2020b; Amster, 2019). Furthermore, coal mining strongly damages the local environment, for example turning entire landscapes into open pit mines or leading to groundwater degradation. Coal thus has high environmental and social costs that are mostly not reflected in prices. Studies show that phasing out coal yields substantial local environmental and health benefits that outweigh direct policy costs (Rauner et al., 2020a).

Phasing-out freely emitting coal – particularly in the power sector – is therefore done first and rather rapidly in many emission reduction scenarios (Clarke et al., 2014). Early retirement of coal infrastructures is a common feature of pathways that limit global warming to well 2°C. For example, Fofrich et al. (2020) suggest in a multi-model study that coal power infrastructure would need to be retired on average 30 years earlier (range: 19-34) than the historical averages of 39 years when following 1.5°C pathways and 23 (11-33) years earlier when following 2°C pathways. Cui et al. (2019) arrive at similar, but slightly more conservative estimates for coal power plants, but only consider the existing and currently proposed capacity.

However, there are significant economic and political barriers to rapidly phasing out coal

(Edwards, 2019; Zhao and Alexandroff, 2019; Jakob et al., 2020; Diluiso et al., 2021). Coal is abundant and allows for cheap extraction. Coal infrastructure is long-lived and retiring this infrastructure would lead to stark reductions on the return of investment and could lead to stranded assets in some cases. Coal has also often been associated with stimulating economic growth and regional development. Apart from these economic barriers, there are social and political ones, too. Coal is often deeply rooted in the culture of coal regions and communities. Stakeholders from the coal industry are well connected and can often mobilize strong lobbying power to protect their vested interests. Some of these reasons may explain why major coal producers have – so far – been rather hesitant to retire their coal power fleet. For example, Jewell et al. (2019) highlight that premature retirement of power plants pledged by members of the Powering Past Coal Alliance would cut emissions by 1.6 GtCO2, which is less than 1% of future CO2 emissions from existing coal power plants. Climate negotiations at the COP26 in Glasgow have also focused on phasing out coal to keep the 1.5°C target within reach. Even though more and more countries pledge to shut down their existing coal-fired power plants or at least end planning and construction of new ones (COP26, 2021), current pledges are not yet sufficient for ambitious climate mitigation (Center for Research on Energy and Clean Air, 2021).

Policy makers therefore need to design policy packages that overcome these barriers to reduce carbon emissions in coal-intensive energy systems and reap co-benefits for public health. Additionally, phase-out policies need to prevent new lock-ins, for example into natural gas, to keep climate goals in reach.

This study looks at the coal phase-out in Germany and the role of the Coal Commission that was formed by the government as a means to reach a decision on how to manage the phase-out. The Coal Commission, composed of a broad range of stakeholders from climate science, NGOs, industry associations as well as policymakers from the affected regions, was tasked to recommend key elements of how a phase-out could be organized in a just way without leaving people and regions behind. This study focuses on public reactions to this policy process and assesses whether the use of multi-stakeholder commissions like the Coal Commission as a mediating form of policy-making has an effect on public opinion on the coal topic.

Public opinion is traditionally measured by conducting surveys to get representative views of the population. While single surveys might be easier to implement, they lack information on how opinions change over time – a crucial part of the information for explaining policy change. On the contrary, panel surveys are very resource intensive, need to be planned well in advance and are nevertheless limited in following real-time responses to policy making. They are also typically conducted over a lengthy period of time, making it difficult to extract real-time responses and opinions on trending issues (Klašnja et al., 2018).

One alternative to this is to measure public opinion using social media data. Social media provide an opportunity to examine public opinion without any prompting or framing effects from analysts. The data is fine-grained and allows for detailed temporal analysis, which is useful for tracking decision-making processes such as the Coal Commission, which span a period of time with different significant events occurring at different stages (Cody et al., 2015; Klašnja et al., 2018). This comes with the downside of not being representative of the population (Mislove et al., 2011; Mellon and Prosser, 2017).

In this paper, we use microblogs from Twitter to analyze public opinion about the coal phase-out in Germany. Twitter is an online service that allows users to easily publish and spread short messages, so-called tweets or microblogs, of up to 280 characters. It is used by a variety of actors in political, business, scientific and other public debates. This highly granular data allows for observations on swiftly changing temporal patterns in public opinion. On the one hand, the interest in discussing coal phase-out and related issues can function as a proxy to track the change in salience of the topic. On the other hand, the data can reveal different positions, lines of argument and emotions driving the discussion. In addition, Twitter is commonly used as a source of information about breaking news events, and journalists and traditional media often solicit feedback from the public through social media. This presents an opportunity to study the public opinion about a topic through looking at tweets.

Research with Twitter data has increased dramatically in recent years because the data is easy to access and covers a huge variety of topics. Twitter data has been used, for example, to study media attention and information spreading (Cao et al., 2012; Lin et al., 2013; Lin et al., 2014), political attention (Hemphill and Roback, 2014; Shapiro and Hemphill, 2017), and political responsiveness (Barberá et al., 2019). It is also often used in the analysis of public opinion on political issues (DiGrazia et al., 2013; Vaccari et al., 2013; Barberá et al., 2019) and the study of political networks (Cherepnalkoski and Mozetič, 2016).

Several studies have examined various aspects of the debate on climate change and climate policies on Twitter. For example, Cody et al. (2015) use sentiment analysis as a method of unsolicited public opinion polling on climate change and find that sentiment changes in response to specific event types. Jang and Hart (2015) study common frames associated with climate change on Twitter and find stark differences in their geographical dispersion. Williams et al. (2015) conduct a network analysis on the climate change debate on Twitter, classifying active users in the dataset based on their expressed attitude towards climate change as “activists”, “sceptics”, or “neutral”. The authors find that most users only interact with other like-minded users. Messages between like-minded users carried mostly positive sentiments, while messages between sceptics and activists carried negative sentiment. Other studies have researched the impact of weather on tweets, for example linking expressed sentiment to mental health problems (Baylis et al., 2018; Obradovich et al., 2018) or studying the remarkability and thus public perception of temperature anomalies (Moore et al., 2019).

In this article, we aim to identify whether the Coal Commission process affected public opinion about the German coal exit on Twitter. Specifically, we want to answer the following research question: **Did the establishment of a multi-stakeholder, corporatist process like the Coal Commission lead to more public consensus on Twitter?** To do so, we apply different measures of polarity in public opinion.

The following Section 2 of this paper reviews background information about coal politics in Germany and the history of the so-called Coal Commission, on which much of the analyzed Twitter debate focuses. Section 3 then introduces the methods and data employed in our analysis, which is presented in Section 4. The paper concludes with a discussion of the results and policy implications in Sections 5 and 6.

2 The German Coal Commission

Coal-fired power plants produced a third of German electricity in 2019 (Arbeitsgemeinschaft Energiebilanzen e.V., 2019), while contributing to more than 70% of emission from the power sector (Umweltbundesamt, 2022). The coal industry in Germany operates both lignite and hard coal power stations. Hard coal mining in Germany peaked in 1958 and was subsidized until its final phase-out in 2018 because Germany could not compete with world market prices (Oei et al., 2019). Today, all hard coal is imported, while lignite production in opencast pit mines is still active due to low extraction costs (Brauers et al., 2020; Appunn, 2019). However, the European emissions trading scheme (EU ETS) obliges power plant operators to purchase allowances for their CO2 emissions, which are especially high for burning lignite. With tightening climate goals and the need to reduce emissions faster, public and policy debates on the phase-out of all coal-fired electricity generation increased over the last two decades (Leipprand and Flachsland, 2018; Osička et al., 2020; Müller-Hansen et al., 2021).

In 2018, the German government comprising Chancellor Angela Merkel's Christian Democratic Union (CDU, including the Bavarian CSU) and the Social Democrats (SPD) agreed in their coalition agreement to set up a special commission consisting of different stakeholders to develop a plan to manage the phase-out of coal-fired power plants in Germany (Wehrmann, 2018). Against the backdrop of Germany looking likely to miss its 2020 climate targets (Bundesregierung der Bundesrepublik Deutschland, 2017), and increasing international pressure for stronger climate action, the political goal was to reduce CO2 emissions while ensuring grid stability and supply security in the transition period, develop an economic perspective for coal-dependent regions and give power plant operators guidance for their planning.

Multi-stakeholder commissions have informed policy making in the Federal Republic of Germany since at least the 1960s as part of the "negotiation democracy" (Lehmbruch, 2000, Verhandlungsdemokratie). They are an instrument for incorporating expertise and interests from different groups into political decision-making. Depending on the policy field, representatives of business, science, the social partners, churches, associations and political parties are appointed for a limited time period to give recommendations or negotiate a compromise on a specific policy problem (Krick, 2013; Siefken, 2016). Even though the number of commissions in German policy making is not exactly known, their number presumably did not grow during the last decades. However, media attention and funding increased, which may explain the perceived increase in political decisions guided by such commissions (Siefken, 2016). Examples of multi-stakeholder commissions in environmental policy decision-making in Germany include the ethics commission for the second nuclear phase-out decision (Ethik-Kommission Sichere Energieversorgung, 2011), the commission for finding a deep geological repository for radioactive waste (Kommission Lagerung hoch radioaktiver Abfallstoffe, 2016) and the "Commission to Review the Financing for the Phase-out of Nuclear Energy" (Kommission zur Überprüfung der Finanzierung des Kernenergieausstiegs, 2016).

The German government under the lead of the Federal Ministry for Economy and Energy (BMWi) gave the "Commission on Growth, Structural Change and Employment", as it was formally named, the mandate to develop a consistent plan to gradually reduce coal-fired power generation. This included the necessary accompanying legal, economic and structural measures to implement the phase-out and to deal with its environmental and social impacts (Groll, 2019). The commission comprised key stakeholders from businesses and industries, the trade unions, energy industry, as well as representatives from coal-mining regions in Germany, the Parliament, administration, environmental NGOs, and scientists (Agora Energiewende and Aurora Energy Research, 2019).

The Coal Commission was formally established on June 6, 2018, and first met on June 26, 2018. Nine meetings on roughly a monthly basis followed and concluded with the closing meeting on January 25, 2019. In addition to discussions between members, the Commission listened to technical experts from the Federal Government, the Federal States, industry, trade unions, science, and civil society (Wehrmann, 2018). On January 26, 2019, the Commission published its findings in a final report. One of the key recommendations from the commission's report was to set a deadline to phase-out coal – by shutting down existing coal-fired power plants step by step until 2035, or 2038 by the latest. The commission recommended to support the regions affected by the coal phase-out with a structural transition fund amounting to around 40 billion euros (Egenter and Wehrmann, 2019). Following the release of the Coal Commission's report (BMWi, 2019), the German cabinet adopted its coal exit law in January 2020 (Wettengel, 2020). The German Bundestag approved the final version after small modifications in July 2020. The law roughly implements the commission's recommendations but exceeds the recommended phase-out path as well as the total remaining emissions. Löw Beer et al. (2021) and Gürtler et al. (2021) provide more details on the Coal Commission's sequence of events and an evaluation of its political legitimacy.

In the accompanying public debate, criticisms emerged about the process and outcome of the Coal Commission. The recommendations are not consistent with the Paris Climate Agreement (Sommer, 2019), nor do they help Germany to meet its own climate targets. It has been framed as a victory for the coal regions and industries, but the final report, dubbed the "coal compromise", has been criticised by environmental activists for not reflecting a consensus (Busse, 2019; Ende Gelände, 2019).

The approach of installing a multi-stakeholder commission has also been criticized, as the commission presented its recommendations as a direct policy prescription, which falsely assumes that such a prescription is value-neutral (Kowarsch, 2019). The commission could have been mandated to present several options including their implications as opposed to one clear-cut phase-out solution to better serve democratic decision-making. Other critiques have been raised towards the misrepresentation of different interest groups (Kern and Meier, 2018). During implementation of the recommendations, the compensation, especially for lignite power plants, has been criticized for being far too high for facilities that will likely become unprofitable in the near future (Götze, 2020). The German Coal Commission thus presents a unique situation for analysing the interplay between the "corporatist" process of such a multi-stakeholder commission and public debates.

3 Methods and data

3.1 Twitter data

The data used in this project were collected directly from Twitter API v2 through Academic Research access to which we applied for this project. All data collection, pre-processing, and analysis was done using the programming language Python. The collection of tweets consists of all German-language tweets that include terms directly related to the coal exit in Germany, in particular "Kohlekommission" (Coal Commission), "Kohleausstieg" (coal exit) and "Kohlefrei" (coal free). We included all tweets from the period January 1, 2017 to February 29, 2020.

An additional set of tweets on climate was collected as a baseline for comparison. This set includes all tweets with the search terms "Klima" (climate), "Erderwärmung" (global warming), "globale Erwärmung" (global warming), and "Treibhauseffekt" (greenhouse effect).

The coal dataset consists of 557,530 tweets, of which 155,148 are original tweets and 402,382 are retweets. They have been sent from 139,669 different users. The total number of tweets in the climate dataset is 1,803,022 with 714,089 original tweets and 1,088,933 retweets.

The data processing and analysis was conducted according to a Data Management Protocol, considering ethical recommendations specifically for Twitter data (Williams et al., 2017; Gold, 2020). It has been reviewed and approved by the Ethics Office of Hertie School (approval number 09-05-22-1). The data used in this paper was finally updated on May 30 and 31, 2022.

3.2 Sentiment Analysis

A major focus of our analysis is on the sentiment expressed in tweets on coal in the German debate. Sentiment analysis refers to methods from natural language processing that systematically identify and extract affective states and subjective information in text. There are different approaches to sentiment analysis in the literature, based on dictionaries, supervised machine-learning, or a mix of knowledge-based and statistical methods (see for example Kumar and Jaiswal (2020) and Cambria et al. (2013) for reviews of sentiment analysis approaches).

Dictionary or lexical approaches usually score texts based on words associated with emotions or valuation. Dictionaries are used to assign polarity weights to words occurring in the text and these sentiment scores for individual words are then aggregated. Sentences or documents can be evaluated on one or several dimensions, for example summing up all negative and all positive word scores separately or just adding them up. For example, Dodds et al. (2011) developed a tool for measuring expressed happiness via positive and negative sentiment in large text corpora. Other commonly used approaches based on word lists are LIWC (Tausczik and Pennebaker, 2010), SentiWordNet (Esuli and Sebastiani, 2006), and SentiStregth (Thelwall et al., 2010), some of which have been compiled using machine learning methods.

Approaches based primarily on supervised learning use the input of manually labelled data in order to train a classifier and then predict the sentiment of a larger set of unlabelled data. This method is used for example by Stukal et al. (2019), who apply neural networks to classify the political orientation of "bots" (automated posters) on Twitter. Other commonly used machine-learning methods for sentiment analysis include SASA (Wang et al., 2012), PANAS-t (Gonçalves et al., 2013b), and SenticNet (Cambria et al., 2010).

Here, we use the simple dictionary approach called SentiWS, a publicly available German-language resource for sentiment analysis (Remus et al., 2010). Entries in the SentiWS dictionary set have four components: the word, its Part of Speech (POS) tag, a polarity weight, and inflections associated with the word. The polarity weights are scaled to the interval [-1;1] and rounded to 4 decimal places with +1.0 being absolutely positive and -1.0 being absolutely negative. The weights of word entries in SentiWS are retrieved using a method known as Pointwise Mutual Information (PMI) (Church and Hanks, 1990; Turney and Littman, 2003).

To obtain the sentiment score of a tweet, denoted by s_{tweet}, we take the average sentiment score of all words in a tweet, using the following formula:

$$s_{tweet} = \frac{\sum_{i=1}^{n} s_i f_i}{\sum_{i=1}^{n} f_i}, \tag{1}$$

where s_i is the polarity weighting score of a word i given in SentiWS, and f_i is the frequency of occurrence of this word in the tweet. We select this approach because it allows for a straight-forward analysis and has the specific advantage that changes over time can be analyzed in depth (see next subsection). Furthermore, other analyses have shown that results are reproducible with other dictionary-based approaches (Baylis et al., 2018).

3.3 Word Shift Analysis

We analyze how the language and sentiment changed over time, employing "word valence shift graphs", first used in Dodds et al. (2011). Building upon the analysis of tweet sentiment scores, word shift graphs show the variation between the sentiment scores of two sets of texts. In these graphs, words are ranked by their descending absolute contribution to the change in average sentiment score in one set of texts relative to another.

The approach for finding the absolute contributions is conducted at the word-level. If we consider two sets of texts, reference (r) and comparison (c) with average scores of $\bar{s}_{\mathrm{r}}$ and $\bar{s}_{\mathrm{c}}$, respectively, the differences of these averages can be written as:

$$\bar{s}_{\mathrm{c}} - \bar{s}_{\mathrm{r}} = \sum_{i=1}^{N} s_i p_i^{\mathrm{c}} - \sum_{i=1}^{N} s_i p_i^{\mathrm{r}} = \sum_{i=1}^{N} s_i \left(p_i^{\mathrm{c}} - p_i^{\mathrm{r}} \right), \tag{2}$$

where $p_i^{\mathrm{c/r}}$ are the normalized frequencies of occurrence of the word i in the comparison and reference text sets, $p_i = f_i / \sum_{j=1}^{N} f_j$ with frequencies f_i. Equation 2 shows that this difference can be decomposed into contributions from single words, which are determined (a) by the weight s_i and (b) by the difference in the relative frequencies $p_i^{\mathrm{c}} - p_i^{\mathrm{r}}$. For producing the word shift graphs, we therefore rank the absolute value of contributions $|s_i \left(p_i^{\mathrm{c}} - p_i^{\mathrm{r}} \right)|$ for each word and show only those words with the strongest contributions to the difference. Furthermore, we indicate how the sign of each contribution is determined by the sign of its word score s_i and the sign of the difference in normalized frequencies.

3.4 Network analysis

We construct and analyze retweet networks to further understand polarization of the coal debate on Twitter. A retweet refers to a re-post of a tweet: another user chooses to share another user's tweet on their personal timeline. By taking Twitter users as nodes and retweets as edges, we can construct a retweet network and see which users retweet the most often from other users. This network shows which users interact with respect to content that they share or comment. Compared to networks based on follower relationships, retweet networks depend on interactions in a specific time period, which make them especially suitable for comparisons across different time periods.

The community structure of a network describes the appearance of densely connected groups of vertices, with only sparse connections between groups (Newman, 2006). The goal of community detection algorithms, implicit or explicit, is to find the best trade-off between a large intra-cluster link density and a small inter-cluster link density. The strength of a community structure can be measured by its modularity, which is a measure of the extent to which clusters are connected internally compared to links between clusters in a network. It takes a value that is strictly less than 1, and it is positive if there are more edges between vertices of the same group than would be expected by chance, and negative if there are less (Newman, 2006). Modularity is defined as:

$$Q = \frac{1}{2m} \sum_{i,j} \left(A_{ij} - \frac{k_i k_j}{2m} \right) \delta(c_i c_j), \tag{3}$$

where m is the total number of edges in the network, A_{ij} are the elements of the adjacency matrix, or the number of edges between vertices i and j, c_i is the label of the community to which the node i is assigned, and k_i is the degree of node i.

Most community detection algorithms apply strategies to partition the network into different communities that maximize modularity. Good algorithms thus find partitions of the network with low modularity, i.e. comparatively few edges between communities. In this study, we use the fast-greedy and multilevel community detection algorithms (Clauset et al., 2004; Blondel et al., 2008). Fast-greedy is a popular algorithm for large networks due to its low computational cost. It operates via hierarchical agglomeration. One of its limitations is that it tends to quickly form large communities at the expenses of small ones (Fortunato, 2010). The multilevel algorithm uses heuristics to move nodes between communities and agglomorates communities such that modularity is maximized. We also tested the selected algorithms against a few other ones (Walk trap, infomap, leading eigenvector) and found that they resulted in the highest modularity scores.

4 Results

The discussion on coal in the German Twitter sphere increased in terms of tweet counts over the years, as Fig. 1 shows. In the period before the establishment of the Coal Commission, there were on average only 200 tweets on coal per day. This number more than tripled for the period between the establishment and finalization of the Coal Commission (742 tweets/day) and the

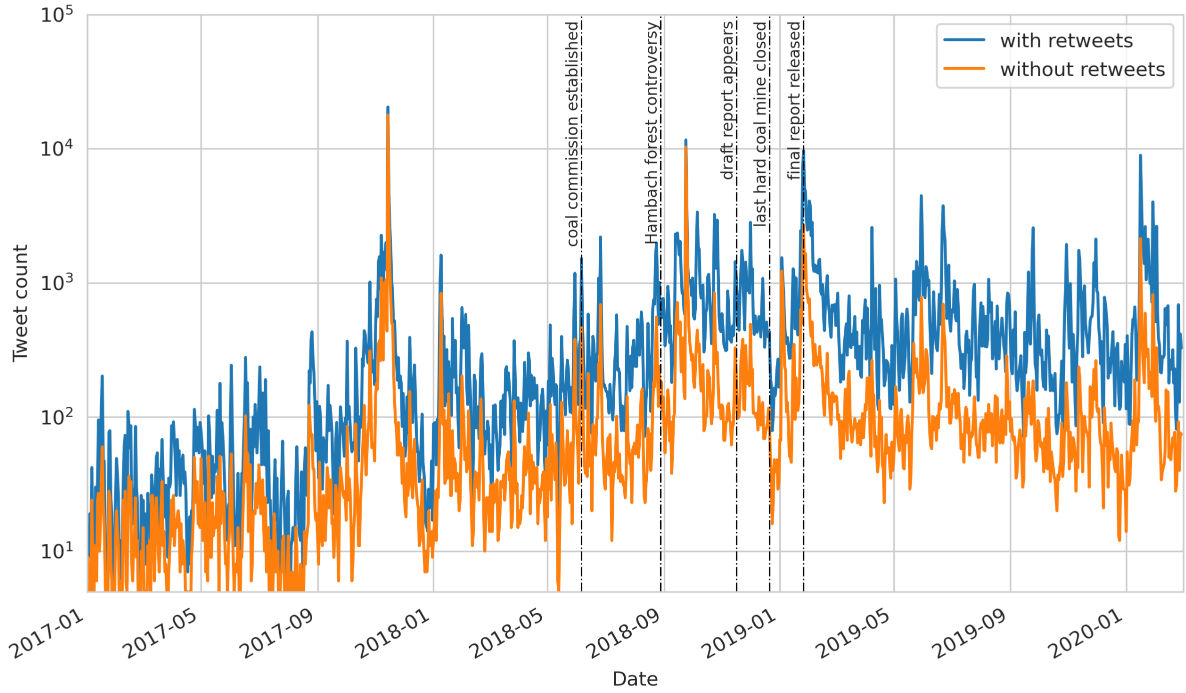
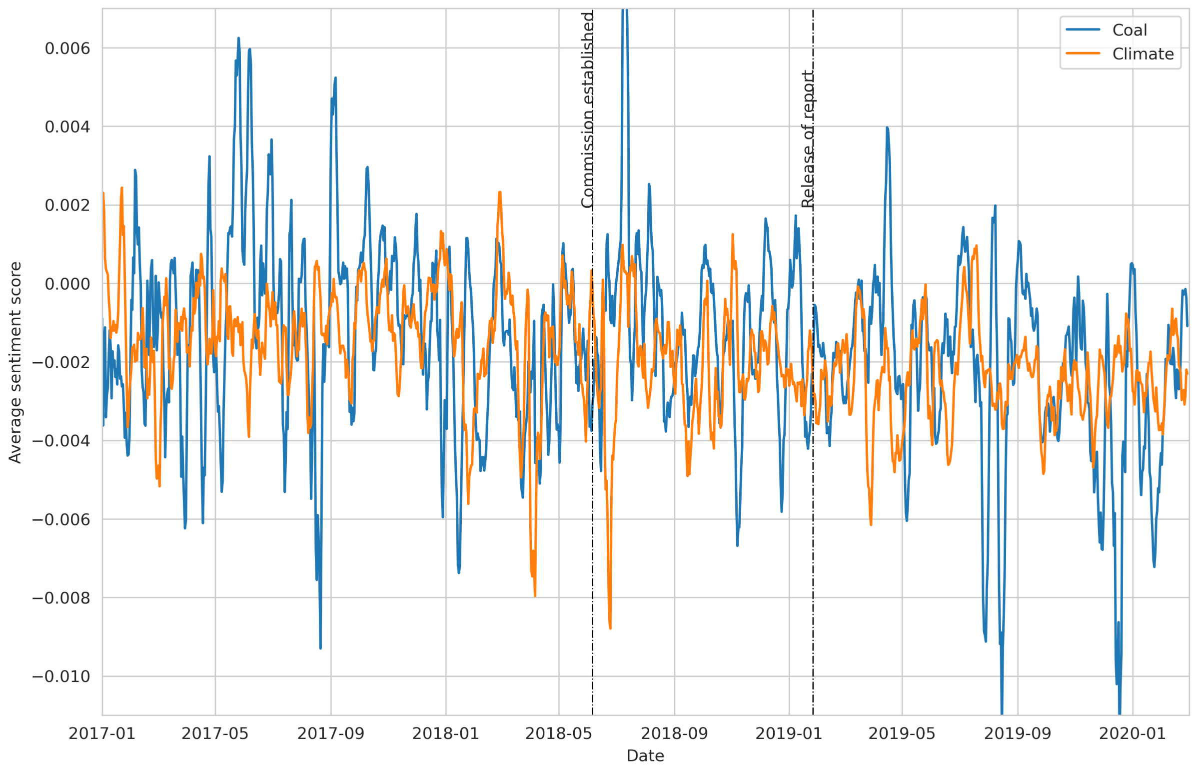


Figure 1: Daily count of German coal related tweets before, during and after the Coal Commission.
The tweet counts are displayed on a log scale to better account for the different magnitudes between peaks and daily baseline activity.

time after the release of the report (699). Thus, the number of tweets indicates that the Coal Commission was accompanied by an increase in attention to the topic on Twitter. This increase in attention co-occurred with a growing interest in climate issues in the German Twitter debate growing from an average of 492 tweets per day in 2017 to more than 3300 in 2019.

Fluctuations in tweet numbers in Fig. 1 highlight the importance of events that strongly drive attention on Twitter. The release of the Coal Commission reports marks such an event and reflects the public interest given to the report in Germany. Over the reported time period it marks one of the three major peaks in attention triggering 9,637 tweets on January 26, 2019. Only two events saw even higher levels of attention to coal: In mid November 2017, an online climate march organised by Fridays for Future demanded an end to coal-fired power plants in Germany (among other things), resulting in 20,420 tweets related to coal, and in September 2018, the controversy about the expansion of an open pit mine into an old forest area, the Hambach forest in North Rhine-Westphalia, peaked with 11,610 tweets per day.



7-day moving averages of sentiment scores from coal and climate tweets. Both time series show a negative trend over time.

4.1 Declining sentiment scores and increasing polarization

The language used in both coal and climate discussions on Twitter becomes on average more negative over time. Fig. **??** shows the 7-day moving average of sentiment scores in the coal and climate datasets. Regression analysis reveals that the average scores of both coal and climate tweets decrease. The regression coefficients are -3.5×10^{-6} and -1.1×10^{-6} sentiment points per day for the coal and climate tweets respectively. These trends are highly significant ($p < 0.001$). The comparison between both trends shows that the coal debate grew more than three times faster negative than the climate debate.

Sentiment peaks are driven by opinionated and highly retweeted tweets. Fig. **??** shows spikes in the average sentiment scores over time. A manual analysis of the tweets underlying the positive peaks reveals that these are mostly driven by original tweets with high positive sentiment scores that were frequently retweeted. Some of them use irony or sarcasm to express positions against the coal compromise. Negative spikes are mostly related to tweets containing negative comments on the Coal Commission's work or on events in coal politics related to the commission. With the exception of some positive outliers, the findings from tweets related to peaks in the sentiment time series are well in line with the negative trend in sentiments over time.

Table 1: Measures of variation in sentiment scores of coal and climate tweets and their counts in different time periods: before establishment of the commission (Jan 2017 to Jun 2018), session of the commission (Jun 2018 to Jan 2019), before the commission's report (i.e. the two former combined), after the report (Jan 2019 - Feb 2020).

		Period				
Measure	Sample	before est.	session	before report	after report	entire
Tweet count	coal	104279	173651	277930	279600	557530
	climate	248911	223567	472478	1330544	1803022
Standard deviation ($\times 10^{-2}$)	coal	1.17	1.33	1.27	1.45	1.37
	climate	1.62	1.68	1.65	1.61	1.62
Mean absolute deviation ($\times 10^{-3}$)	coal	6.20	7.34	6.92	9.11	8.06
	climate	8.93	10.64	9.77	10.03	9.97

In addition to the trend in the time series, we find that measures of variation of the sentiments expressed in tweets about coal increase over time, as Table 1 shows. While the standard deviation of all sentiment scores is especially high during the session of the Coal Commission, this cannot be observed for the mean absolute deviation, where the period after the release of the report has the highest value. Table 1 also shows that measures of variation are even higher for the climate dataset, which indicates that this debate is more emotional than the one on coal.

This shift can also be observed when looking at histograms of the sentiment scores by time periods. Fig. 2 compares histograms of sentiment scores for tweets in the coal dataset before and after the release of the Coal Commission report. It does not only convey that more tweets carry a sentiment different from zero but also shows that both positive and negative sentiments become more prevalent after the release compared to before. We observe similar developments for the variation of sentiment scores in the sample of climate tweets.

Overall, our analysis of the sentiment scores of the coal and climate debate on Twitter reveals that they have both negative trends and their variation increases over time. However, the effect is much larger for the coal debate.

4.2 Increasing proportions of negative and positive words

In order to understand what drove the sentiment change over time, we split the dataset into two periods – before the release of the Coal Commission's final report and after. The tweets

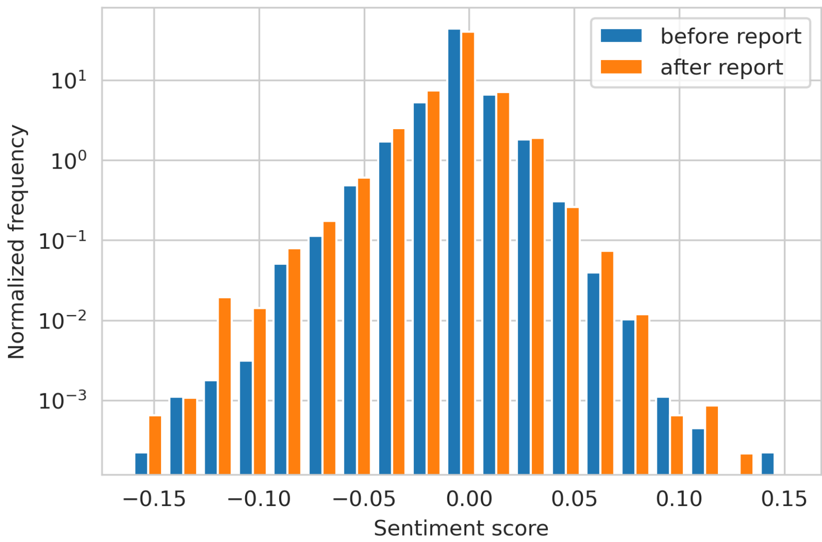


Figure 2: Normalized histogram of tweet sentiment from coal tweets before and after the release of the Coal Commission report.

that were posted after the release of the report are then analyzed in comparison to the tweets that were posted before the report's release using the decomposition of contributions of single word to changes in average sentiment.

As detailed in Section 3.3, we identify the words with the greatest influence on differences in average sentiment scores between the two periods. Fig. 3 shows the 35 words ranked by their contribution to this difference, with the color indicating their polarity. Most of the words carry strong sentiment, which is why the product of a difference in word frequencies between both periods contributes more to the difference in sentiment scores. Furthermore, most of the words have a negative polarity and increased from the first to the second period (e.g. mistake, criticism, expensive, fear, etc.) such that they contribute to the observed overall negative difference. Some cases of positive words that saw an increase (e.g. fair, good, want, fun, etc.) and negative words that decreased (e.g. give up, destroy, dispute, etc.) counteract this overall effect. The changing frequencies in the 35 words shown in Fig. 3 explain about 40% of the average difference in word scores between the two periods.

The split in the balance of scores arising from positive and negative words, before and after the release of the Coal Commission's report, also suggest that there is an increase in polarisation of sentiments on Twitter after the Coal Commission process (Fig. 4).

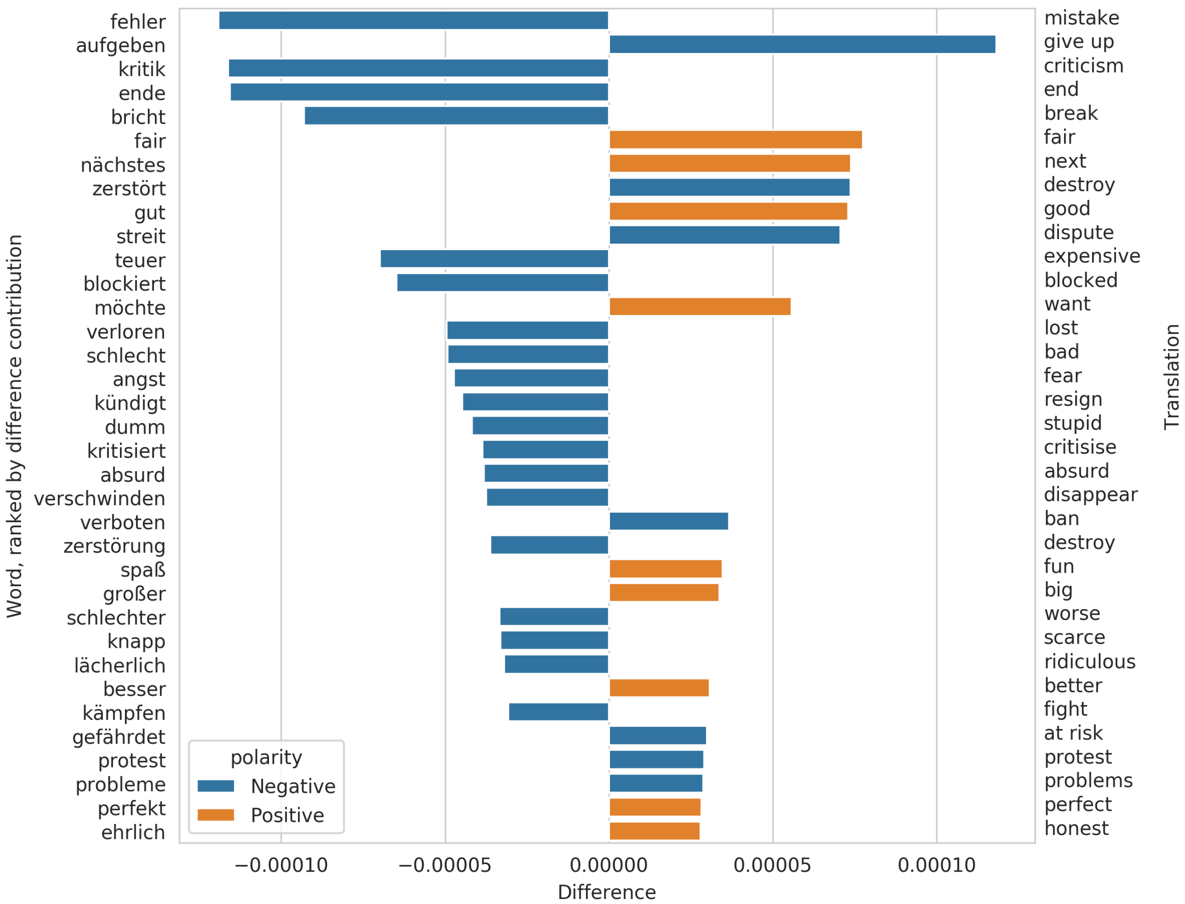


Figure 3: Word shift graph comparing tweets posted before and after the release of the report of the Coal Commission. Orange bars indicate words with positive polarity scores. Blue bars indicate words with negative polarity scores. Words with a bar pointing to the right side are contributing to an increase in average sentiment, while words with a bar on the left contribute to a decrease in average sentiment.

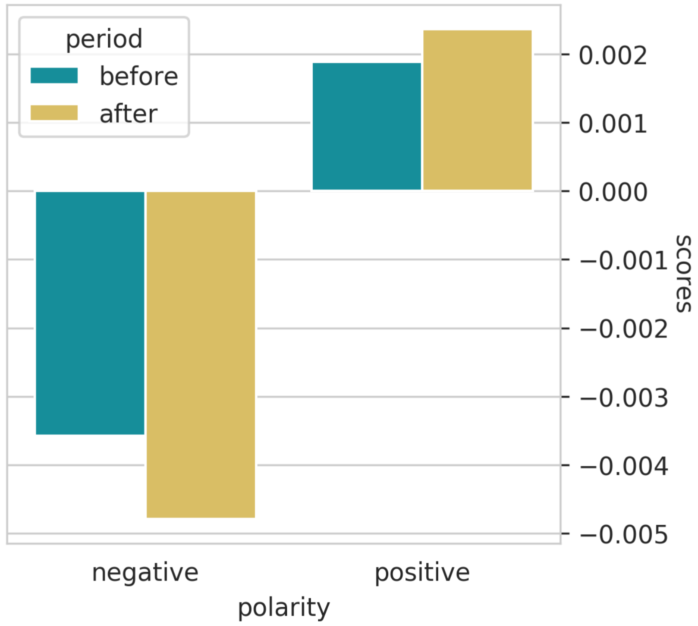


Figure 4: Average sentiment scores of words before and after the release of the Coal Commission report, sorted by polarity.

4.3 Increasing modularity of retweet networks

For the network analysis, we constructed three different retweet networks: (1) using the coal tweets for the period before the release of the report (Jan 2017 to Jan 2019), (2) using the ones after the report's release (Feb 2019 - Feb 2020), and (3) all coal tweets in our sample.

Table 2 lists the modularity scores for the networks that we computed as explained in Sect. 3.4. The modularity scores for all networks lie between 0.4 and 0.5, corresponding to a network structure in which communities only partially separate, with quite some interactions between them. Studies show that the modularity score of large-scale social networks is often greater than 0.5 (Blondel et al., 2008). This suggests that the community structure of the retweet network of the German coal debate on Twitter is not particularly strong.

More importantly, the modularity scores of the retweet networks from after the report are larger than those of the the network from before the report. This is true for the two different algorithms we employed and suggests that there was less interaction between different communities after the Coal Commission finished its report relative to the total number of interactions. As above, this is another indication that the Coal Commission did not yield more consensus in the public debate on Twitter. While the number of nodes, i.e. users that retweet content, increased only slightly by 2%, the number of edges increased by more than 26%. Thus,

Table 2: Size, density and modularity scores of coal retweet networks before and after the release of the Coal Commission's report and for the entire dataset.

	Period		
	before report	after report	entire
Nodes	46594	47592	78149
Edges	97854	123964	210089
Density	9.0e-5	1.1e-4	6.9e-5
Modularity (fast-greedy)	0.415	0.438	0.409
Modularity (multilevel)	0.424	0.437	0.422

the Coal Commission process and related events generated more interactions in total, while relatively decreasing interactions between communities.

5 Discussion

This study aims to identify whether the German Coal Commission effected public debates on the German coal exit. Based on our analysis, we conclude that the public debate on Twitter was indeed driven by events around the Coal Commission, even though social movements such as Fridays for Future and EndeGelände also had strong influence. During the sessions of the commission, the number of tweets increased strongly and especially the release of the report triggered strong responses on Twitter. More than 14% of the original tweets in our dataset relate explicitly to the Coal Commission. Nevertheless, it is difficult to quantify the influence of the Coal Commission on the overall debate as there is no way to build a counterfactual without this influence.

We observe a clear negative trend of average sentiment scores throughout the entire period of study from January 2017 to February 2020 as well as a polarization of sentiments over time. Additionally, our network analysis reveals an increasing modularity and thus proportionally less references between communities. If the coal compromise would have led to a stronger consensus on Twitter, we would expect that sentiments would get more positive and less polarized over time. Also, retweeting between different communities would increase. We therefore conclude that our empirical observations points to less consensus on Twitter. However, this conclusion needs to acknowledge some limitations of our method and data that we discuss in the following.

5.1 Limitations of automated sentiment analysis

The results of the sentiment analysis method rely on the quality of the dictionary and the context for which the scores were computed (Gonçalves et al., 2013a). The pre-made, publicly available German dictionary SentiWS used here is a general resource, and not uniquely created for the context of studying the coal debate on Twitter. As a result, the words available in the dictionary may not reflect the full spectrum of words used in the coal debate, nor does it account for slang, which is common on social media networks but is rarely supported in dictionaries (Hu et al., 2013). By design, dictionary approaches to sentiment analysis do not take the context of words into account and can therefore easily misclassify the overall sentiment of a text. However, in line with other research, we assume that such errors are averaged out for our large datasets (Dodds et al., 2011; Baylis et al., 2018).

Some of these limitations are evident from the results presented. Our manual analysis of positive spikes in the sentiment time series revealed that some of the tweets were sarcastic or ironic and were indeed critical about coal use. As all computational analyses lead to simplified sentiment classification, manual validation is necessary to check results. However, our analysis suggests that the negative sentiment is even more pronounced than what our automated analysis found.

One way of better integrating information from the context of the words in a tweet would be to use machine learning methods. Such methods often rely on supervised classification approaches, where sentiment detection is framed as a binary or ternary variable (i.e. positive, negative or neutral). Supervised approaches require labeled data to train classifiers (Pang et al., 2002). This is advantageous as it allows for flexibility in creating trained models for specific purposes and contexts, but also has the drawback that labeled data may not be available for a specific domain or language and can contain errors. On the one hand, existing labeled data may often be ill suited for training classifiers that perform well on texts from a specific domain, as for example in the case of applying training data from standard long-form text to analyze social media text. On the other hand, manually labeling training data sets can be time intensive and costly.

Even though a method such as the one applied here cannot fully represent human sentiment expressed in texts, they have the advantage that they work out of the box and thus ease automation and speed up the analysis. Although it is important to acknowledge that tweet sentiment is represented simplistically, and in some individual cases even inaccurately, we crossvalidated that the main result of our analysis is plausible at the aggregate level.

We also acknowledge that sentiments do not coincide with positions (stances) in a political debate. However, we decided to use sentiments rather than stance in this analysis because they are easy to detect and give some information about the emotionality of a debate. Stance detection (Abercrombie and Batista-Navarro, 2020) needs a lot of contextual information and is therefore difficult to implement for tweet classification. However, future research could use several tweets from a time period and user to identify her position on an issue.

5.2 Public opinion and social media

While using social media data from Twitter offers many benefits compared to conventional surveys in measuring public opinion, there are also several limitations. Firstly, the assumption that Twitter posts represent an honest expression of public opinion may not necessarily hold true. The public nature of social media could induce a stronger social desirability bias compared to traditional survey responses, but the extent to which this occurs is unknown (Klašnja et al., 2018).

In comparison to traditional surveys, one crucial advantage that is lost with social media is the opportunity to control the sampling frame. In analyzing public opinion on social media, researchers do not ask the "respondents" a question, but rather depend on participants to reveal their opinion. For social media, however, the likelihood that someone has been asked a "question" is not known, nor the likelihood of a response (Klašnja et al., 2018). Thus, it is difficult to compare social media data with opinions revealed in surveys because the set of people offering unprompted opinions on a topic may be more passionate, knowledgeable, extrovert, or different in many other ways compared to a representative sample of a population who offer opinions on a topic when explicitly asked.

Furthermore, Twitter users are not representative of national populations, as is well documented (Duggan et al., 2015; Mislove et al., 2011; Malik et al., 2015; Mellon and Prosser, 2017; Fernández et al., 2014). In the United States, it has been found that the most populous counties are overrepresented (Mislove et al., 2011), and there are also significant biases towards younger users and users of higher income when comparing geotagged tweets and census data (Malik et al., 2015). Twitter users tend to hold more extreme ideological viewpoints (Barberá and Rivero, 2015), which is consistent with more extreme views being voiced on Twitter. We therefore caution against generalizing the results of our paper to the national coal debate, as there is not enough information about the user demographics on Twitter to be able to make these generalizations.

Twitter also need not reflect a balance of all opinions voiced by different stakeholders in a debate. The evidence in the literature shows different degrees of agreement between opinions expressed on Twitter and public opinions as elicited in polls, with many studies finding considerable overlap (Thapen and Ghanem, 2013; Anuta et al., 2017; Oliveira et al., 2017; Klingeren et al., 2021).

The general trends that we identify in this study are in line with results from representative surveys and panels. For recent years, they find that public support for coal as an energy source is low compared to other energy sources and has further declined over time (Schumann et al., 2016; Nippa, 2015). They also show that coal is mainly perceived negatively in the general population (Nippa and Lee, 2014). This aligns well with our finding that the average sentiment score of tweets related to coal is negative and declining. Further analyses on the type of users, their roles in public discourse and their underlying demographics is needed to better relate analyses such as ours to other research, for example on traditional media and representative surveys.

6 Conclusion and policy implications

This study provides an overview of the German coal discourse on the social media site Twitter by analyzing the sentiments and retweet networks related to coal phase-out debates. Twitter has gained importance as both a channel of information spreading and a public space for policy debates and is therefore an interesting resource for understanding public opinion dynamics. The results show that there is a negative trend in the sentiment of tweets over time, in parallel with the broader German debate on climate. The sentiment scores' variation also increases over time, suggesting that more emotional language has been used and the debate became more polarized over time. Further analysis of the content of tweets associated with peaks in average daily sentiment shows that negative language is being used to express the severity of climate change, and the role that coal plays in it. The Coal Commission is also, by extension, painted in a negative light. Additionally, the analysis of retweet networks reveals that the relative interaction between communities decreased. Despite the intention of the Coal Commission process to bring together different stakeholders in the coal sector to come to a common result for the coal phase-out in Germany, this aim of consensus-building did not extend to the public on Twitter.

These findings have several policy implications. Online discourses on coal are dominated by negative views on coal. This is likely due to the increase in calls for greater climate action as part of the Fridays For Future movement that gained traction over the year 2019. Environmental policies will be scrutinized by online communities, and policies that may be perceived to not prioritize the environment enough are likely to cause strong reactions. Given the attention that Twitter discussions also receive in traditional media, this is important for policy makers to bear in mind even if online discussions could be biased towards opposing views. Whilst policy-making should not only be based on popularity, it is nevertheless important for policy-makers to understand sentiments on the ground, and how policies will be received when introduced and enacted. This is particularly true for future planning, as many climate and environmental policies will only deliver positive results in the long term if they have large public support.

Another policy implication pertains to our observation that the coal commission did not foster more consensus in the coal debate on Twitter. The increase in both the variation of sentiment scores as well as the increase of positive and negative words during the Coal Commission process suggest that the debate intensified, at least emotionally. While the commission eventually agreed on a final phase-out date, as well as the amount for structural funds to support those affected by the phase-out, many observers saw this as a poor compromise, and multiple criticisms of the commission's report have since been launched. It can therefore be doubted that the societal conflicts around the contentious issues of phasing out coal have successfully been pacified.

While multi-stakeholder commissions may be useful in bringing together stakeholders with different interests, results may not necessarily lead to more consensus in the wider public. Hence, such commissions should not necessarily be seen as a means for building public consensus on a topic. In contrast, rather than contributing to consensus on an issue within the broader public they may even fuel fiercer debates, as a topic gets more media attention through the work of a commission. Of course, stronger attention could also have been caused by a traditional policy decision and in the case of the coal phase-out question could have fuelled the debate even more.

In summary, the ongoing and polarized discussion about the future of coal in Germany is not surprising given the lack of input, throughput and output legitimacy of the commission (Löw Beer et al., 2021). More open forms of public participation, such as citizen councils and deliberative forums (Garard et al., 2018; Beauvais and Warren, 2019; Pfeifer et al., 2020), should therefore be considered as alternative or supplemental ways to obtain policy advice that improve the public legitimacy of policies.

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No potential competing interest was reported by the authors.

Data and code availability

The code to reproduce the analysis and figures is publicly available from [link to public github repository will be included here before publication]. The Twitter data is subject to copy rights and thus cannot be openly shared. However, we provide a list of tweet IDs in the repository above.

References

Abercrombie, G. and R. Batista-Navarro (2020). "Sentiment and position-taking analysis of parliamentary debates: a systematic literature review". In: *Journal of Computational Social Science* 3.1, pp. 245–270. DOI: 10.1007/s42001-019-00060-w.

Agora Energiewende and Aurora Energy Research (2019). *The German Coal Commission. A Roadmap for a Just Transition from Coal to Renewables.* Tech. rep. URL: https://static.agora-energiewende.de/fileadmin/Projekte/2019/Kohlekommission_Ergebnisse/168_Kohlekommission_EN.pdf (visited on Dec. 21, 2021).

Amster, E. (2019). "Public health impact of coal-fired power plants: a critical systematic review of the epidemiological literature". In: *Int. J. Environ. Health Res.* 31.5, pp. 558–580. DOI: 10.1080/09603123.2019.1674256.

Anuta, D., J. Churchin, and J. Luo (2017). "Election Bias: Comparing Polls and Twitter in the 2016 U.S. Election". URL: http://arxiv.org/abs/1701.06232.

Appunn, K. (2019). *Coal in Germany.* Clean Energy Wire. URL: https://www.cleanenergywire.org/factsheets/coal-germany (visited on Dec. 21, 2021).

Arbeitsgemeinschaft Energiebilanzen e.V. (2019). *Stromerzeugung nach Energieträgern (Strommix) von 1990 bis 2018 (in TWh) Deutschland insgesamt.* URL: https://ag-energiebilanzen.de/daten-und-fakten/bilanzen-1990-bis-2019 (visited on Dec. 21, 2021).

Barberá, P., A. Casas, J. Nagler, P. J. Egan, R. Bonneau, J. T. Jost, and J. A. Tucker (2019). "Who Leads? Who Follows? Measuring Issue Attention and Agenda Setting by Legislators and the Mass Public Using Social Media Data". In: *American Political Science Review* 113.4, pp. 883–901. DOI: 10.1017/S0003055419000352.

Barberá, P. and G. Rivero (2015). "Understanding the Political Representativeness of Twitter Users". In: *Social Science Computer Review* 33.6, pp. 712–729. DOI: 10.1177/0894439314558836.

Baylis, P., N. Obradovich, Y. Kryvasheyeu, H. Chen, L. Coviello, E. Moro, M. Cebrian, and J. H. Fowler (2018). "Weather impacts expressed sentiment". In: *PLoS One* 13.4, e0195750. DOI: 10.1371/journal.pone.0195750.
Beauvais, E. and M. E. Warren (2019). "What can deliberative mini-publics contribute to democratic systems?" In: *Eur. J. Polit. Res.* 58.3, pp. 893–914. DOI: 10.1111/1475-6765.12303.
Blondel, V. D., J.-L. Guillaume, R. Lambiotte, and E. Lefebvre (2008). "Fast unfolding of communities in large networks". In: *Journal of Statistical Mechanics: Theory and Experiment* 2008.10, P10008. DOI: 10.1088/1742-5468/2008/10/P10008.
BMWi (2019). *Kommission "Wachstum, Strukturwandel und Beschäftigung" Abschlussbericht.* Tech. rep. URL: https://www.bmwi.de/Redaktion/DE/Downloads/A/abschlussbericht-kommission-wachstum-strukturwandel-und-beschaeftigung.pdf (visited on Dec. 21, 2021).
Brauers, H., P. Y. Oei, and P. Walk (2020). "Comparing coal phase-out pathways: The United Kingdom's and Germany's diverging transitions". In: *Environmental Innovation and Societal Transitions* 37.August, pp. 238–253. DOI: 10.1016/j.eist.2020.09.001.
Bundesregierung der Bundesrepublik Deutschland (2017). *Projektionsbericht 2017 für Deutschland gemäß Verordnung (EU) Nr. 525/2013.* URL: https://cdr.eionet.europa.eu/de/eu/mmr/art04-13-14_lcds_pams_projections/projections/envwqc4_g/170426_PB_2017_-_final.pdf (visited on Dec. 21, 2021).
Busse, S. (2019). *"Ein Schlag ins Gesicht".* Klimareporter. URL: https://www.klimareporter.de/protest/ein-schlag-ins-gesicht (visited on Dec. 21, 2021).
Callaghan, M., C. F. Schleussner, S. Nath, Q. Lejeune, T. R. Knutson, M. Reichstein, G. Hansen, E. Theokritoff, M. Andrijevic, R. J. Brecha, M. Hegarty, C. Jones, K. Lee, A. Lucas, N. van Maanen, I. Menke, P. Pfleiderer, B. Yesil, and J. C. Minx (2021). "Machine-learning-based evidence and attribution mapping of 100,000 climate impact studies". In: *Nat. Clim. Chang.* 11.11, pp. 966–972. DOI: 10.1038/s41558-021-01168-6.
Cambria, E., B. Schuller, Y. Xia, and C. Havasi (2013). "New Avenues in Opinion Mining and Sentiment Analysis". In: *IEEE Intell. Syst.* 28.2, pp. 15–21. DOI: 10.1109/MIS.2013.30.
Cambria, E., R. Speer, C. Havasi, and A. Hussain (2010). "SenticNet: A Publicly Available Semantic Resource for Opinion Mining". In: *AAAI Fall Symp. Ser. 2010 AAAI Fall Symp. Ser.* URL: https://www.aaai.org/ocs/index.php/FSS/FSS10/paper/view/2216.
Cao, N., Y. Lin, X. Sun, D. Lazer, S. Liu, and H. Qu (2012). "Whisper: Tracing the Spatiotemporal Process of Information Diffusion in Real Time". In: *IEEE Trans. Vis. Comput. Graph.* 18.12, pp. 2649–2658. DOI: 10.1109/TVCG.2012.291.
Center for Research on Energy and Clean Air (2021). *Powering Down Coal – COP26's Impact on the Global Coal Power Fleet.* Tech. rep. URL: https://energyandcleanair.org/wp/wp-content/uploads/2021/11/Glasgow-impact-on-coal.pdf (visited on Dec. 23, 2021).
Cherepnalkoski, D. and I. Mozetič (2016). "Retweet networks of the European Parliament: evaluation of the community structure". In: *Appl. Netw. Sci.* 1.1, p. 2. DOI: 10.1007/s41109-016-0001-4.
Church, K. W. and P. Hanks (1990). "Word Association Norms, Mutual Information, and Lexicography". In: *Computational Linguistics* 16.1, pp. 22–29. URL: https://www.aclweb.org/anthology/J90-1003.
Clarke, L., K. Jiang, K. Akimoto, M. Babiker, G. Blanford, K. Fisher-Vanden, J.-C. Hourcade, V. Krey, E. Kriegler, A. Löschel, D. McCollum, S. Paltsev, S. Rose, P. Shukla, M. Tavoni, B. van der Zwaan, and D. P. van Vuuren (2014). "Assessing Transformation Pathways". In: *Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change.* Ed. by O. Edenhofer, R. Pichs-Madruga, Y. Sokona, E. Farahani, S. Kadner, K. Seyboth, A. Adler, I.

Baum, S. Brunner, P. Eickemeier, B. Kriemann, J. Savolainen, S. Schlömer, C. von Stechow, T. Zwickel, and J. C. Minx. Cambridge, UK, and New York: Cambridge University Press.
Clauset, A., M. E. J. Newman, and C. Moore (2004). "Finding community structure in very large networks". In: *Phys. Rev. E* 70.6, p. 66111. DOI: 10.1103/PhysRevE.70.066111.
Cody, E. M., A. J. Reagan, L. Mitchell, P. S. Dodds, and C. M. Danforth (2015). "Climate Change Sentiment on Twitter: An Unsolicited Public Opinion Poll". In: *PLOS ONE* 10.8, e0136092. DOI: 10.1371/journal.pone.0136092.
COP26 (2021). *End of Coal in Sight at COP26.* URL: https://unfccc.int/news/end-of-coal-in-sight-at-cop26 (visited on Dec. 23, 2021).
Cui, R. Y., N. Hultman, M. R. Edwards, L. He, A. Sen, K. Surana, H. McJeon, G. Iyer, P. Patel, S. Yu, T. Nace, and C. Shearer (2019). "Quantifying operational lifetimes for coal power plants under the Paris goals". In: *Nat. Commun.* 10.1, p. 4759. DOI: 10.1038/s41467-019-12618-3.
DiGrazia, J., K. McKelvey, J. Bollen, and F. Rojas (2013). "More Tweets, More Votes: Social Media as a Quantitative Indicator of Political Behavior". In: *PLoS One* 8.11, e79449. DOI: 10.1371/journal.pone.0079449.
Diluiso, F. et al. (2021). "Coal transitions - Part 1: A systematic map and review of case study learnings from regional, national, and local coal phase-out experiences". In: *Environ. Res. Lett.* 16.11, p. 113003. DOI: 10.1088/1748-9326/ac1b58.
Dodds, P. S., K. D. Harris, I. M. Kloumann, C. A. Bliss, and C. M. Danforth (2011). "Temporal Patterns of Happiness and Information in a Global Social Network: Hedonometrics and Twitter". In: *PLOS ONE* 6.12, e26752. DOI: 10.1371/journal.pone.0026752.
Duggan, M., N. B. Ellison, C. Lampe, A. Lenhart, and M. Madden (2015). *Social Media Update 2014.* Tech. rep. Pew Research Center. URL: https://www.pewresearch.org/internet/2015/01/09/social-media-update-2014/ (visited on Dec. 21, 2021).
Edenhofer, O., J. C. Steckel, M. Jakob, and C. Bertram (2018). "Reports of coal's terminal decline may be exaggerated". In: *Environ. Res. Lett.* 13, p. 024019. DOI: 10.1088/1748-9326/aaa3a2.
Edwards, G. A. S. (2019). "Coal and climate change". In: *WIREs Climate Change* 10.5, e607. DOI: 10.1002/wcc.607.
Egenter, S. and B. Wehrmann (2019). *German commission proposes coal exit by 2038.* Clean Energy Wire. URL: https://www.cleanenergywire.org/factsheets/german-commission-proposes-coal-exit-2038 (visited on Dec. 21, 2021).
Ende Gelände (2019). *Pressestatement vom 26.01.2019.* Ende Gelände. URL: https://www.ende-gelaende.org/press-release/pressestatement-vom-26-01-2019/ (visited on Dec. 21, 2021).
Esuli, A. and F. Sebastiani (2006). "SENTIWORDNET: A Publicly Available Lexical Resource for Opinion Mining". In: *Proc. Fifth Int. Conf. Lang. Resour. Eval.* Genoa, Italy: European Language Resources Association (ELRA). URL: http://www.lrec-conf.org/proceedings/lrec2006/pdf/384_pdf.pdf.
Ethik-Kommission Sichere Energieversorgung (2011). *Deutschlands Energiewende – Ein Gemeinschaftswerk für die Zukunft.* Tech. rep. URL: https://www.bmu.de/download/deutschlands-energiewende-ein-gemeinschaftswerk-fuer-die-zukunft (visited on Dec. 21, 2021).
Fernández, M., T. Wandhoefer, B. Allen, A. C. Basave, and H. Alani (2014). "Using social media to inform policy making: to whom are we listening?" In: *European Conference on Social Media (ECSM 2014).* URL: http://oro.open.ac.uk/41396/.
Fofrich, R., D. Tong, K. Calvin, H. S. De Boer, J. Emmerling, O. Fricko, S. Fujimori, G. Luderer, J. Rogelj, and S. J. Davis (2020). "Early retirement of power plants in climate mitigation scenarios". In: *Environ. Res. Lett.* 15.9, p. 094064. DOI: 10.1088/1748-9326/ab96d3.
Fortunato, S. (2010). "Community detection in graphs". In: *Phys. Rep.* 486.3, pp. 75–174. DOI: https://doi.org/10.1016/j.physrep.2009.11.002.

Friedlingstein, P., M. W. Jones, M. O. Sullivan, R. M. Andrew, D. C. E. Bakker, J. Hauck, C. L. Quéré, G. P. Peters, and W. Peters (2022). "Global Carbon Budget 2021". In: *Earth System Science Data* 14, pp. 1917–2005. DOI: https://doi.org/10.5194/essd-14-1917-2022.

Garard, J., L. Koch, and M. Kowarsch (2018). "Elements of success in multi-stakeholder deliberation platforms". In: *Palgrave Commun.* 4.1, p. 129. DOI: 10.1057/s41599-018-0183-8.

Gold, N. (2020). *Using Twitter Data in Research - Guidance for Researchers and Ethics Reviewers.* URL: https://www.ucl.ac.uk/data-protection/sites/data-protection/files/using-twitter-research-v1.0.pdf.

Gonçalves, P., M. Araújo, F. Benevenuto, and M. Cha (2013a). "Comparing and Combining Sentiment Analysis Methods". In: *Proc. First ACM Conf. Online Soc. Networks.* COSN '13. New York, NY, USA: Association for Computing Machinery, pp. 27–38. DOI: 10.1145/2512938.2512951.

Gonçalves, P., F. Benevenuto, and M. Cha (2013b). *PANAS-t: A Pychometric Scale for Measuring Sentiments on Twitter.* arXiv: 1308.1857 [cs.SI].

Götze, S. (2020). *Milliardengeschenk für Braunkohlekonzerne.* URL: https://www.spiegel.de/wissenschaft/mensch/kohleausstieg-braunkohlekonzerne-bekommen-bis-zu-zwei-milliarden-geschenkt-a-fdbd8038-7e82-407a-a0ac-b5d11afe1d76 (visited on Dec. 21, 2021).

Groll, S. (2019). *Coal Commission Final Report – Assessment.* Heinrich Böll Stiftung. URL: https://www.boell.de/en/2019/02/18/coal-commission-final-report-assessment (visited on Dec. 21, 2021).

Gürtler, K., D. Löw Beer, and J. Herberg (2021). "Scaling just transitions: Legitimation strategies in coal phase-out commissions in Canada and Germany". In: *Polit. Geogr.* 88, p. 102406. DOI: 10.1016/j.polgeo.2021.102406.

Hemphill, L. and A. J. Roback (2014). "Tweet Acts: How Constituents Lobby Congress via Twitter". In: *Proc. 17th ACM Conf. Comput. Support. Coop. Work Soc. Comput.* CSCW '14. New York, NY, USA: Association for Computing Machinery, pp. 1200–1210. DOI: 10.1145/2531602.2531735.

Hu, X., J. Tang, H. Gao, and H. Liu (2013). "Unsupervised Sentiment Analysis with Emotional Signals". In: *Proc. 22nd Int. Conf. World Wide Web.* WWW '13. New York, NY, USA: Association for Computing Machinery, pp. 607–618. DOI: 10.1145/2488388.2488442.

Jakob, M., C. Flachsland, J. Christoph Steckel, and J. Urpelainen (2020). "Actors, objectives, context: A framework of the political economy of energy and climate policy applied to India, Indonesia, and Vietnam". In: *Energy Res. Soc. Sci.* 70, p. 101775. DOI: 10.1016/j.erss.2020.101775.

Jang, S. M. and P. S. Hart (2015). "Polarized frames on "climate change" and "global warming" across countries and states: Evidence from Twitter big data". In: *Glob. Environ. Chang.* 32, pp. 11–17. DOI: 10.1016/j.gloenvcha.2015.02.010.

Jewell, J., V. Vinichenko, L. Nacke, and A. Cherp (2019). "Prospects for powering past coal". In: *Nat. Clim. Chang.* 9, pp. 592–597. DOI: 10.1038/s41558-019-0509-6.

Kern, V. and F. Meier (2018). *Das sind die Mitglieder der Kohlekommission.* URL: https://www.klimareporter.de/deutschland/das-sind-die-mitglieder-der-kohlekommission (visited on Dec. 21, 2021).

Klašnja, M., P. Barberá, N. Beauchamp, J. Nagler, and J. A. Tucker (2018). "Measuring Public Opinion with Social Media Data". In: *The Oxford Handbook of Polling and Survey Methods.* Ed. by L. R. Atkeson and R. M. Alvarez. Oxford University Press. DOI: 10.1093/oxfordhb/9780190213299.013.3.

Klingeren, M. van, D. Trilling, and J. Möller (2021). "Public opinion on Twitter? How vote choice and arguments on Twitter comply with patterns in survey data, evidence from the 2016 Ukraine referendum in the Netherlands". In: *Acta Politica* 56.3, pp. 436–455. DOI: 10.1057/s41269-020-00160-w.

Kommission Lagerung hoch radioaktiver Abfallstoffe (2016). *Abschlussbericht der Kommission Lagerung hoch radioaktiver Abfallstoffe*. Tech. rep. URL: https://www.bundestag.de/resource/blob/434430/35fc29d72bc9a98ee71162337b94c909/drs_268-data.pdf (visited on Dec. 21, 2021).

Kommission zur Überprüfung der Finanzierung des Kernenergieausstiegs (2016). *Verantwortung und Sicherheit - Ein neuer Entsorgungskonsens*. Tech. rep. URL: https://www.bmwi.de/Redaktion/DE/Downloads/B/bericht-der-expertenkommission-kernenergie.html.

Kowarsch, M. (2019). *Handlungsoptionen statt Entscheidungen*. Tagesspiegel Background. URL: https://background.tagesspiegel.de/energie-klima/handlungsoptionen-statt-entscheidungen (visited on Dec. 21, 2021).

Krick, E. (2013). *Verhandlungen im Konsensverfahren: Varianten kollektiver Entscheidung in Expertengremien*. Wiesbaden: Springer.

Kumar, A. and A. Jaiswal (2020). "Systematic literature review of sentiment analysis on Twitter using soft computing techniques". In: *Concurr. Comput. Pract. Exp.* 32.1, e5107. DOI: 10.1002/cpe.5107.

Lehmbruch, G. (2000). *Parteienwettbewerb im Bundesstaat*. 3rd ed. Wiesbaden, Germany: Westdeutscher Verlag.

Leipprand, A. and C. Flachsland (2018). "Regime destabilization in energy transitions: The German debate on the future of coal". In: *Energy Res. Soc. Sci.* 40, pp. 190–204. DOI: 10.1016/j.erss.2018.02.004.

Lin, Y.-R., B. Keegan, D. Margolin, and D. Lazer (2014). "Rising Tides or Rising Stars?: Dynamics of Shared Attention on Twitter during Media Events". In: *PLoS One* 9.5, e94093. DOI: https://doi.org/10.1371/journal.pone.0094093.

Lin, Y.-R., D. Margolin, B. Keegan, and D. Lazer (2013). "Voices of Victory: A Computational Focus Group Framework for Tracking Opinion Shift in Real Time". In: *Proc. 22nd Int. Conf. World Wide Web*. WWW '13. New York, NY, USA: Association for Computing Machinery, pp. 737–748. DOI: 10.1145/2488388.2488453.

Löw Beer, D., K. Gürtler, J. Herberg, and T. Haas (2021). "Wie legitim ist der Kohlekompromiss? Spannungsfelder und Verhandlungsdynamiken im Prozess der Kohlekommission". In: *Zeitschrift für Polit.* 31.3, pp. 393–416. DOI: 10.1007/s41358-021-00261-8.

Malik, M. M., H. Lamba, C. Nakos, and J. Pfeffer (2015). "Population bias in geotagged tweets". In: *Papers from the 2015 ICWSM Workshop on Standards and Practices in Large-Scale Social Media Research*. ICWSM-15 SPSM. Oxford, UK, pp. 18–27. URL: https://ojs.aaai.org/index.php/ICWSM/article/view/14688.

Mellon, J. and C. Prosser (2017). "Twitter and Facebook are not representative of the general population: Political attitudes and demographics of british social media users". In: *Research and Politics* 4.3, pp. 1–9. DOI: 10.1177/2053168017720008.

Mislove, A., S. Lehmann, Y.-Y. Ahn, J.-P. Onnela, and J. N. Rosenquist (2011). "Understanding the demographics of Twitter users". In: *Proceedings of the International AAAI Conference on Web and Social Media (ICWSM'11)*. Vol. 5. 1, pp. 554–557. URL: https://ojs.aaai.org/index.php/ICWSM/article/view/14168.

Moore, F. C., N. Obradovich, F. Lehner, and P. Baylis (2019). "Rapidly declining remarkability of temperature anomalies may obscure public perception of climate change". In: *Proc. Natl. Acad. Sci.* 116.11, pp. 4905–4910. DOI: 10.1073/pnas.1816541116.

Müller-Hansen, F., M. W. Callaghan, Y. T. Lee, A. Leipprand, C. Flachsland, and J. C. Minx (2021). "Who cares about coal? Analyzing 70 years of German parliamentary debates on coal with dynamic topic modeling". In: *Energy Res. Soc. Sci.* 72, p. 101869. DOI: https://doi.org/10.1016/j.erss.2020.101869.

Newman, M. E. J. (2006). "Modularity and community structure in networks". In: *Proceedings of the National Academy of Sciences* 103.23, pp. 8577–8582. DOI: 10.1073/pnas.0601602103.

Nippa, M. (2015). *Perspektiven der Kohlenutzung in Deutschland – 2014 Meinungsvielfalt trotz Polarisierung.* Tech. rep. URL: https://www.vbgu.de/fileadmin/downloads/AkzeptanzstudieIIkomplett_13.03.2015.pdf (visited on Dec. 21, 2021).

Nippa, M. and R. P. Lee (2014). "Gesellschaftliche Akzeptanz der Kohle und die Zukunft der deutschen Kohleforschung". In: *Chemie-Ingenieur-Technik* 86.10, pp. 1669–1677. DOI: 10.1002/cite.201300190.

Obradovich, N., R. Migliorini, M. P. Paulus, and I. Rahwan (2018). "Empirical evidence of mental health risks posed by climate change". In: *Proc. Natl. Acad. Sci. U. S. A.* 115.43, pp. 10953–10958. DOI: 10.1073/pnas.1801528115.

Oei, P.-Y., H. Brauers, and P. Herpich (2019). "Lessons from Germany's hard coal mining phase-out: policies and transition from 1950 to 2018". In: *Climate Policy* 20.8, pp. 963–979. DOI: 10.1080/14693062.2019.1688636.

Oliveira, D. J. S., P. H. d. S. Bermejo, and P. A. dos Santos (2017). "Can social media reveal the preferences of voters? A comparison between sentiment analysis and traditional opinion polls". In: *Journal of Information Technology and Politics* 14.1, pp. 34–45. DOI: 10.1080/19331681.2016.1214094.

Osička, J., J. Kemmerzell, M. Zoll, L. Lehotský, F. Černoch, and M. Knodt (2020). "What's next for the European coal heartland? Exploring the future of coal as presented in German, Polish and Czech press". In: *Energy Res. Soc. Sci.* 61, p. 101316. DOI: 10.1016/j.erss.2019.101316.

Pang, B., L. Lee, and S. Vaithyanathan (2002). "Thumbs up? Sentiment Classification using Machine Learning Techniques". In: *Proc. 2002 Conf. Empir. Methods Nat. Lang. Process. (EMNLP 2002).* Association for Computational Linguistics, pp. 79–86. DOI: 10.3115/1118693.1118704.

Pfeifer, H., C. Opitz, and A. Geis (2020). "Deliberating Foreign Policy: Perceptions and Effects of Citizen Participation in Germany". In: *Ger. Polit.* 30.4, pp. 485–502. DOI: 10.1080/09644008.2020.1786058.

Ranasinghe, R., A. C. Ruane, R. Vautard, N. Arnell, E. Coppola, F. A. Cruz, S. Dessai, A. S. Islam, M. Rahimi, D. R. Carrascal, J. Sillmann, M. B. Sylla, C. Tebaldi, W. Wang, and R. Zaaboul (2021). "Climate Change Information for Regional Impact and for Risk Assessment". In: *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change.* Ed. by V. Masson-Delmotte, P. Zhai, A. Pirani, S. L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M. I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J. B. R. Matthews, T. K. Maycock, T. Waterfield, O. Yelekçi, R. Yu, and B. Zhou. Cambridge University Press.

Rauner, S., N. Bauer, A. Dirnaichner, R. V. Dingenen, C. Mutel, and G. Luderer (2020a). "Coal-exit health and environmental damage reductions outweigh economic impacts". In: *Nat. Clim. Chang.* 10.4, pp. 308–312. DOI: 10.1038/s41558-020-0728-x.

Rauner, S., J. Hilaire, D. Klein, J. Strefler, and G. Luderer (2020b). "Air quality co-benefits of ratcheting up the NDCs". In: *Clim. Change* 163.3, pp. 1481–1500. DOI: 10.1007/s10584-020-02699-1.

Remus, R., U. Quasthoff, and G. Heyer (2010). "SentiWS - A Publicly Available German-language Resource for Sentiment Analysis". In: *Proceedings of the Seventh International Conference on Language Resources and Evaluation (LREC'10).* Ed. by N. Calzolari, K. Choukri, B. Maegaard, J. Mariani, J. Odijk, S. Piperidis, M. Rosner, and D. Tapias. European Language Resources Association (ELRA). URL: http://www.lrec-conf.org/proceedings/lrec2010/pdf/490_Paper.pdf.

Rogelj, J. et al. (2018). "Scenarios towards limiting global mean temperature increase below 1.5°C". In: *Nat. Clim. Chang.* 8.4, pp. 325–332. DOI: 10.1038/s41558-018-0091-3.

Schleussner, C. F., J. Rogelj, M. Schaeffer, T. Lissner, R. Licker, E. M. Fischer, R. Knutti, A. Levermann, K. Frieler, and W. Hare (2016). "Science and policy characteristics of the

Paris Agreement temperature goal". In: *Nat. Clim. Chang.* 6.9, pp. 827–835. DOI: 10.1038/nclimate3096.

Schumann, D., W. Fischer, and J.-F. Hake (2016). "Kohlenutzung und Kohleausstieg in Deutschland aus Sicht der Bevölkerung". In: *Energiewirtschaftliche Tagesfragen* 6, pp. 18–22.

Shapiro, M. A. and L. Hemphill (2017). "Politicians and the Policy Agenda: Does Use of Twitter by the U.S. Congress Direct New York Times Content?" In: *Policy & Internet* 9.1, pp. 109–132. DOI: 10.1002/poi3.120.

Siefken, S. T. (2016). "Expertenkommissionen der Bundesregierung". In: *Handbuch Politikberatung.* Ed. by S. Falk, M. Glaab, A. Römmele, H. Schober, and M. Thunert. Wiesbaden: Springer Fachmedien Wiesbaden, pp. 1–17. DOI: 10.1007/978-3-658-07461-6_14-1.

Sommer, J. (2019). *Das Versagen der Kohlekommission.* Klimareporter. URL: https://www.klimareporter.de/deutschland/das-versagen-der-kohlekommission (visited on Dec. 21, 2021).

Stukal, D., S. Sanovich, J. A. Tucker, and R. Bonneau (2019). "For Whom the Bot Tolls: A Neural Networks Approach to Measuring Political Orientation of Twitter Bots in Russia". In: *SAGE Open* 9.2. DOI: 10.1177/2158244019827715.

Tausczik, Y. R. and J. W. Pennebaker (2010). "The Psychological Meaning of Words: LIWC and Computerized Text Analysis Methods". In: *J. Lang. Soc. Psychol.* 29.1, pp. 24–54. DOI: 10.1177/0261927X09351676.

Thapen, N. A. and M. M. Ghanem (2013). "Towards Passive Political Opinion Polling using Twitter". In: *CEUR Workshop Proceedings* 1110, pp. 19–34.

Thelwall, M., K. Buckley, G. Paltoglou, and D. Cai (2010). "Sentiment Strength Detection in Short Informal Text". In: *J. Am. Soc. Inf. Sci.* 61.12, pp. 2544–2558. DOI: 10.1002/asi.21416.

Tong, D., Q. Zhang, Y. Zheng, K. Caldeira, C. Shearer, C. Hong, Y. Qin, and S. J. Davis (2019). "Committed emissions from existing energy infrastructure jeopardize 1.5 °C climate target". In: *Nature* 572, pp. 373–377. DOI: 10.1038/s41586-019-1364-3.

Turney, P. D. and M. L. Littman (2003). "Measuring Praise and Criticism: Inference of Semantic Orientation from Association". In: *ACM Trans. Inf. Syst.* 21.4, pp. 315–346. DOI: 10.1145/944012.944013.

Umweltbundesamt (2022). *Entwicklung der spezifischen Treibhausgas-Emissionen des deutschen Strommix in den Jahren 1990 - 2021.* Tech. rep. URL: https://www.umweltbundesamt.de/publikationen/entwicklung-der-spezifischen-kohlendioxid-8.

Vaccari, C., A. Valeriani, P. Barberá, R. Bonneau, J. Jost, J. Nagler, and J. Tucker (2013). "Social media and political communication: A survey of twitter users during the 2013 Italian general election". English (US). In: *Rivista Italiana di Scienza Politica* 43.3, pp. 381–410. DOI: 10.1426/75245.

Wang, H., D. Can, A. Kazemzadeh, F. Bar, and S. Narayanan (2012). "A System for Real-time Twitter Sentiment Analysis of 2012 U.S. Presidential Election Cycle". In: *Proc. ACL 2012 Syst. Demonstr.* Association for Computational Linguistics, pp. 115–120. URL: https://www.aclweb.org/anthology/P12-3020.

Wehrmann, B. (2018). *Germany's coal exit commission.* Clean Energy Wire. URL: https://www.cleanenergywire.org/factsheets/germanys-coal-exit-commission (visited on Dec. 21, 2021).

Wettengel, J. (2020). *Spelling out the coal exit – Germany's phase-out plan.* Clean Energy Wire. URL: https://www.cleanenergywire.org/factsheets/spelling-out-coal-phase-out-germanys-exit-law-draft (visited on Dec. 21, 2021).

Williams, H. T., J. R. McMurray, T. Kurz, and F. H. Lambert (2015). "Network analysis reveals open forums and echo chambers in social media discussions of climate change". In: *Global Environmental Change* 32, pp. 126–138. DOI: https://doi.org/10.1016/j.gloenvcha.2015.03.006.

Williams, M. L., P. Burnap, and L. Sloan (2017). “Towards an Ethical Framework for Publishing Twitter Data in Social Research: Taking into Account Users’ Views, Online Context and Algorithmic Estimation”. In: *Sociology* 51.6, pp. 1149–1168. DOI: `10.1177/0038038517708140`.

Zhao, S. and A. Alexandroff (2019). “Current and future struggles to eliminate coal”. In: *Energy Policy* 129, pp. 511–520. DOI: `https://doi.org/10.1016/j.enpol.2019.02.031`.