Topic and tone of political news articles in German online media.

Franziska Löw*

Department of Industrial Economics,
Helmut Schmidt University,
Hamburg, Germany

April 29, 2019

Abstract

The aim of this paper is to investigate whether the political reporting of different websites differs and whether this reporting has an influence on the voting tendencies. In order to find the latent topics of the news articles, a structural topic model (STM) is estimated. The sentiment value of each article is then examined and the cross-correlation between the sentiment of a political topic and the survey values of the major German parties is calculated. The results show evidence, that the political reporting differs between websites and that the correlation between the sentiment and the poll value is significantly positive, when the reporting about a party is particularly negative.

*Electronic address: loewf@hsu-hh.de

Contents

1 Introduction

The discussion about the influence of digital media on the political opinion-forming process has gained momentum since the presidential elections in October 2016. Overall, the importance of the Internet as a source of information for political topics has been very strong in recent years. According to a study on the media coverage of the German-speaking population, nearly 40% of respondents used the internet at least once a week in 2017 to inform themselves about the current news compared to 34% in 2016.[1]

The pluralism of not only of online media, but media in general is an essential principle of democratic societies. For the opinion forming process, information conveyed by the media, in particular the mass media, plays a decisive role. An important question is therefore whether there are convergence tendencies within the mass media - that is, whether popular media tend to report on certain political topics in the same or similar ways and whether this reporting has an influence on the opinion-forming process of voters. In order to examine the media pluralism in the market for German-language online news, this paper analyzes German online news articles covering domestic politics. German federal elections took place on 24th of September 2017 and the formation of the government has taken up a period of about five months. The articles considered here are dated from June 1, 2017 to March 1, 2018 and thus inform their readers about both the election promises of the parties (before the election) and the coalition talks (after the election). They therefore make an important contribution to the public's opinion-forming process. The empirical strategy follows a novel approach combining "the two Ts": Topic and Tone (Hansen and McMahon, 2016). This means that the topics discussed in the articles are identified first (topic), followed by an analysis of how they are discussed by the various news websites (tone). The final step is to check whether the tonality of reporting is reflected by the survey results on voting preferences calculating the cross correlation coefficients. More precisely, the research strategy is as follows:

1. **Discovering Topics** To discover the latent topics in the news articles, the structural topic modeling (STM) developed by M. E. Roberts, B. M. Stewart, and E. M. Airoldi (2016) is applied. The STM is an unsupervised machine learning approach that models topics as multinomial distributions of words and documents (as a synonym for news articles) as multinomial distributions of topics, allowing the incorporation of external variables that affect both, topical content and topical prevalence. I estimate a model in which the news website is included as a control for the topical prevalence. The results of the generative process of the STM are two posterior distributions: One for the topic prevalence in an article (what is the article about?) and one for the content of a topic (what is the topic about?). The latter is used to label the topics according their most common words and the former is used to assign a topic to each news article.

2. **Measuring Tone** After assigning a topic to each article, a dictionary-based sentiment analysis is conducted to estimate how topics are discussed differently by different news websites. To conduct such an analysis, a list of words (dictionary) associated with a given emotion, such as negativity is pre-defined. The document is then deconstructed into individual words and each word is assigned a sentiment value according to the dictionary, where the sum of all values results in the emotional score for the given document.

[1] Verbrauchs- und Medienanalyse - VuMA 2018: https://www.vuma.de/vuma-praxis/die-studie/

3. **Comparing with polls** In order to check whether the transmitted content from the online media is reflected in the voting preferences, the relationship between monthly average of the emotional score of individual topics from 2 and the poll results of a specific party is estimated using the cross correlation function (CCF).

Approach 1 has been used in M. E. Roberts, B. M. Stewart, and E. M. Airoldi (2016), among others, to examine differences in the content of eastern and western news providers regarding "the rise of China". However, I extend the analysis by comparing the sentiment scores for a given topic at different news providers, to identify which topics are discussed similarly or differently (2). Hansen and McMahon (2016) applied a similar approach to a dataset of 142 Federal Open Market Committee (FOMC) decision statements to measure the effect of those statements on macroeconomic variables. An additional extension is the comparison with current election poll values (3).

The remaining course of the paper is as follows: The following section gives an overview of political trends in the past six month (June 2017 to March 2018). The data used to conduct the model is described in section 3. Section 4 explains the generative process of the structural topic model as well as the selected parameters to run the model. The empirical analysis containing the above-mentioned steps is conducted in section 5.

2 Background on the federal election in Germany (2017)

The articles analyzed in this paper cover a period from June 1, 2017 to March 1, 2018 and thus cover both the most important election campaign topics for the Bundestag elections on September 24, 2017 and the process of forming a government that lasted until February 2018. After four years in a grand coalition with the Social Democrats (SPD), German Chancellor Angela Merkel, member of the conservative party CDU/CSU (also known as Union), ran for re-election. The SPD nominated Martin Schulz as their candidate.

On the right side of the political spectrum, AfD (alternative for Germany) managed to be elected to the German Bundestag for the first time in 2017. The political debate about the high refugee numbers of the past years brought a political upswing to the AfD, which used the dissatisfaction of parts of the population to raise its own profile. In the course of the reporting on the federal elections, leading party members of the AfD as well as party supporters repeatedly accused the mass media of reporting unilaterally and intentionally presenting the AfD badly.

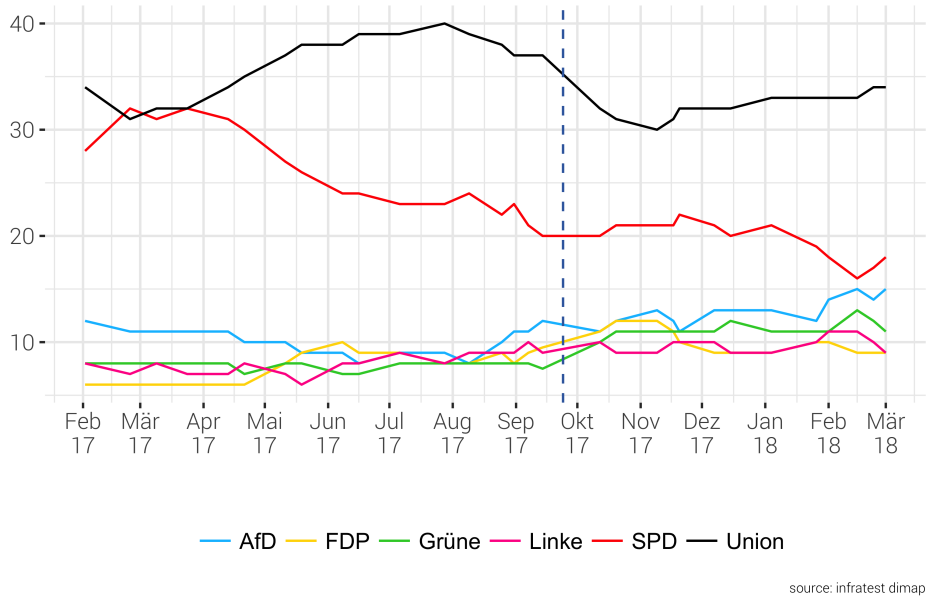
After the election, the formation of a government was difficult due to the large number of parties elected to the Bundestag and the considerable loss of votes by the major parties CDU/CSU and SPD. Since all parties rejected a coalition with the AfD, numerically only two coalitions with an absolute parliamentary majority were possible: a grand coalition ("GroKo" - from the German word Große Koalition) of CDU/CSU and SPD, and a Jamaica coalition (coalition of CDU/CSU, FDP (economic liberal party) and B90/Die Grünen (Bündnis 90/Die Grünen, green party)). The grand coalition was initially rejected by the SPD. The four-week exploratory talks on the possible formation of a Jamaica coalition officially failed on November 19, 2017 after the FDP announced its withdrawal from the negotiations. FDP party leader Christian Lindner said that there had been no trust between the parties during the negotiations. The main points of contention were climate and refugee policy. CDU and CSU regretted this result, while B90/Die Grünen sharply criticized the liberals' withdrawal. The then Green leader Cem Özdemir accused the FDP of lacking the will to reach an agreement.

After the failure of the Jamaica coalition talks, a possible re-election or a minority government as alternatives were discussed in the media before the SPD decided to hold

coalition talks with the CDU/CSU. This led to great resistance from the party base, which called for a party-internal referendum on a grand coalition. After the party members voted in favor of the grand coalition, a government was formed 171 days after the federal elections.

Figure 1 shows that support for the two major popular parties has been declining in recent months since August 2017, with the CDU/CSU again showing positive survey results since November 2017. However, the poll results of the SPD have been falling since March 2017. At the same time, the AfD in particular has been recording increasingly positive survey results since June 2017. Section 5.3 examines whether there is a correlation between the survey results and the way the parties are reported about the media.

Figure 1: Election Polls



3 Dataset and data preparation

I conduct the estimation on a sample of 14,937 online news articles from seven German news providers about domestic politics[2]. The articles are dated from June 1, 2017 to March 1, 2018. I first extract all online articles using the Webhose.io API.[3] Then all articles from the section "domestic policy" are filtered by using the URL of an article. Overall, the selected news providers are among the top ten German online news providers - in terms of unique user[4] - in the period under review, with only Tagesschau.de belonging to the public media. The reason for this is that the content structure of Tagesschau.de is most similar to that of the private providers. ZDF.de offers predominantly video content and DLF (Deutschlandfunk) website mainly offers audio content in the form of interviews, which makes it hard to include it in the model.

Figure 2a shows the distribution of the number of articles by date. There is a high peak around the federal elections on September, 24th and another one shortly after the

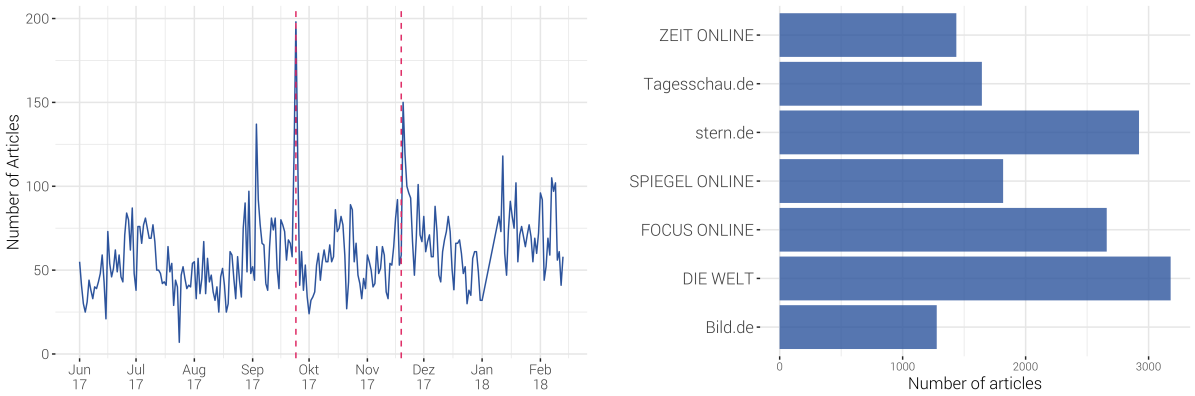
[2]Bild.de, DIE WELT, FOCUS ONLINE, SPIEGEL ONLINE, stern.de, ZEIT ONLINE, Tagesschau.de

[3]For more information see https://docs.webhose.io/v1.0/docs/getting-started. The scraping code was written in Python and can be made available on request.

[4]The term unique user refers to a number of different visitors to a website within a certain period of time. Multiple visits from the same user are only considered once.

failure of the Jamaica coalition talks on November, 19th (indicated by the red dotted lines). Figure 2b shows that DIE WELT published the most articles on domestic policy, followed by stern.de and FOCUS ONLINE.

Figure 2: Article distribution...

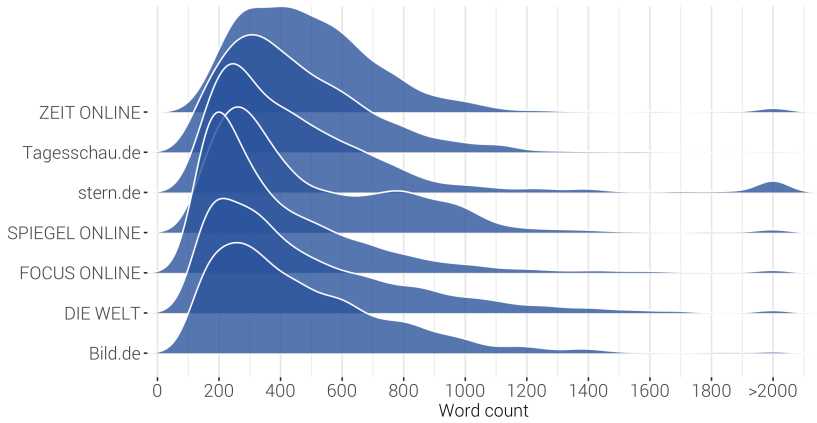


(a) ...by date

(b) ... by news provider

Looking at the histograms of the text length (Figure 3), it becomes evident that most of the articles have a word length between 200 and 1000 words (articles with less than 200 words were filtered out in advance, as these were mostly reader comments). The distribution at Bild.de, DIE WELT, FOCUS ONLINE and stern.de is left-skewed, whereby stern.de has many articles with a word length of over 2000 in comparison.

Figure 3: Text length



The longest article at Tagesschau.de contains 2006 words, nevertheless the median value is comparatively large (see table). ZEIT ONLINE has the highest median value of 459 words.

To summarize the content of the texts, wordclouds help to get a first impression, as they represent the frequency of words by their size. Intuitively the term frequency (tf) of a word is a measure of how important that word may be for the understanding of the text. The word cloud in Figure 4 is derived from all articles within the dataset. As can be seen, problems arise with words that are highly frequent. For example "die", or

Table 1: Summary statistics of text length

	group1	n	mean	sd	median	min	max	se
1	Bild.de	1277.00	475.20	319.22	394.00	121.00	3710.00	8.93
2	DIE WELT	3179.00	507.88	614.28	377.00	121.00	14507.00	10.89
3	FOCUS ONLINE	2660.00	402.68	330.86	299.00	121.00	5647.00	6.42
4	SPIEGEL ONLINE	1817.00	498.96	333.23	387.00	121.00	3304.00	7.82
5	stern.de	2922.00	518.09	622.99	376.50	121.00	9287.00	11.53
6	Tagesschau.de	1644.00	450.34	242.93	397.50	121.00	2006.00	5.99
7	ZEIT ONLINE	1437.00	510.98	377.85	459.00	121.00	8015.00	9.97

"der (eng. "the"), "und" (eng. "and"), and "ist" (eng. "is") are extremely common but unrelated to the quantity of interest. These terms, often called stop words (Gentzkow et al., 2017), are important to the grammatical structure of a text, but typically don't add any additional meaning and can therefore be neglected. A common strategy to reduce the number of language elements is to pre-process the text by imposing some preliminary restrictions (e.g. stop-word removal and stemming) based on the nature of the data (twitter text, newspaper articles, speeches, etc.) (ibid.). In fact, in order to use text as data and reduce the dimensionality to avoid unnecessary computational complexity and overfitting, pre-processsing the text is a central task in text mining (Bholat et al., 2015).

Figure 4: Wordcloud (before pre-processing)

Stemming is a process by which different morphological variants of a word are traced back to their common root. For example, "voting" and "vote" would be treated as two instances of the same token after the stemming process. There are many different

techniques for the stemming process. I apply the widely used Porter-Stemmer algorithm, which is based on a set of shortening rules that are applied to a word until it has a minimum number of syllables.[5] To remove distorting words, the pre-defined stop word list from the Snowball project[6] is used together with a customized list of stop-words. Additionally punctuation character (e.g. ., „ !, ?, etc.) and all numbers are removed from the data. After completing these steps we were left with 68,576 unique terms in our vocabulary. The following wordclouds represent the most frequent words of the pre-processed articles for Bild.de and Tagesschau.de.[7] It becomes evident that these are texts discussing domestic policy issues. The SPD in particular seems to be highly frequent. However, at first glance, there are no obvious differences between the news providers.

Figure 5: Wordclouds (after pre-processing)

(a) Bild.de

(b) Tagesschau.de

To use text as data for statistical analysis, the next step is to divide the entire dataset into individual documents and to represent these documents as a finite list of unique terms. In this setting, each news article represents a document d, whereby each of these documents can be assigned to a news website. The sum of all documents forms what is called the corpus. For each document $d \in \{1, ..., D\}$ the number of occurrences of term v in document d is computed, in order to obtain the count $x_{d,v}$, where each unique term in the corpus is indexed by some $v \in \{1, ..., V\}$ and where V is the number of unique terms. The D x V matrix $\boldsymbol{X}$ of all such counts is called the document-term matrix. Each row in this matrix represents a document, where each entry in this row counts the occurrences of a unique term in that document. This representation is often referred to as the bag of words model (Gentzkow et al., 2017), since the order in which words are used within a document is disregarded.

[5] https://tartarus.org/martin/PorterStemmer/

[6] http://snowball.tartarus.org/algorithms/german/stop.txt

[7] The wordclouds of the other parties can be found in the appendix A.1

4 The structural topic model

To find out the latent structure of each document, a structural topic model (STM) is estimated. In general, topic models formalize the idea that documents are formed by hidden variables (topics) that generate correlations among observed terms. They belong to the group of unsupervised generative models, meaning that the true attributes (topics) cannot be observed. One crucial assumption to be made for such models is the number of topics (K) that occur over the entire corpus.

Each individual topic potentially contains all of the unique terms within the vocabulary V with different probability. Therefore, each topic k can be represented as a probability vector ϕ_k over all unique terms V. Simultaneously, each individual document d in the corpus can be represented as a probability distribution θ_d over the K topics. To generate each individual word $w_{d,n}$ in a document d for the n^{th} word-position, a topic allocation $z_{d,n}$ is drawn from the topic distribution for that document θ_d. Then, a word is drawn from the term distribution for the selected topic $\phi_{z_{d,n}}$.[8]

The STM developed by M. E. Roberts, B. M. Stewart, and E. M. Airoldi (2016) is a recent extension of the standard topic modeling technique, labeled as latent Dirichlet allocation (LDA), which refers to the Bayesian model in Blei et al. (2003) that treats each word in a topic and each topic in a document as generated from a Dirichlet - distributed prior.[9] Since its introduction into text analysis, LDA has become hugely popular and especially useful in political science.[10] Wiedmann (2016) uses topic model methods on large amounts of news articles from two german newspapers published between 1959 and 2011, to reveal how democratic demarcation was performed in Germany over the past six decades. Paul (2009) compares editorial differences between media sources, using cross-collection latent Dirichlet allocation (ccLDA), an LDA-based approach that incorporates differences in document metadata. They use a dataset of 623 news articles from August 2008 from two American media outlets - msnbc.com and foxnews.com - to compare how they discuss topics. Reviewing the top words of the word-topic distribution, they find some content differences between the two media sources under review.

The STM allows to incorporate document specific covariates (e.g. the author or date of a document). The model has been applied to multiple academic fields: M. E. Roberts, B. M. Stewart, Tingley, et al. (2014) uses STM to analyze open-ended responses from surveys and experiments, Farrell (2016) applies the model to scientific texts on climate change, revealing links between corporate funding and the framing of scientific studies. Mishler et al. (2015) show that "STM can be used to detect significant events such as the downing of Malaysia Air Flight 17" when applied to twitter data. Another study shows how STM can be used to explore the main international development topics of countries' annual statements in the UN General Debate and examine the country-specific drivers of international development rhetoric (Baturo et al., 2017). Mueller and Rauh (2016) use newspaper text to predict armed conflicts in different regions. They use the estimated topic shares in linear fixed effects regression to forecast conflict out-of-sample. M. Roberts, B. Stewart, and Tingley (2016a) use STM to examine the role of partisanship in topical coverage using a corpus of 13,246 posts that were written for 6 political blogs during the course of the 2008 U.S. presidential election. With the aim of revealing the effect of partisan membership on topic prevalence, each blog is assigned to

[8] A more detailed description of the generative process of the STM can be found in section 4.1

[9] See also Griffiths and Steyvers (2002), Griffiths and Steyvers (2004) and Hofmann (1999). Pritchard et al. (2000) introduced the same model in genetics for factorizing gene expression as a function of latent populations.

[10] see Blei (2012), Grimmer and B. Stewart (2013) and Wiedmann (2016) for an overview in social science and Gentzkow et al. (2017) give an overview of text mining applications in economics.

be either liberal or conservative. To explore the differences between the two, they look at the expected proportion of topics and examine the posts most associated with a respective topic. This approach is similar to M. E. Roberts, B. M. Stewart, and E. M. Airoldi (2016).

4.1 Generative Process of STM

As mentioned above, the STM allows to incorporate observed document metadata which is able to affect both topical prevalence and topical content. These assumptions are reflected in the prior distributions. The following describes the generative process for filling the n^{th} word-position in document d in the case of the STM (M. Roberts, B. Stewart, Tingley, and E. Airoldi, 2013): As in the case of conventional models, first a specific topic z_{dn} is assigned, according to the topic distribution for that document θ through the process:

$$z_{dn}|\theta_d \sim \text{Multinomial}(\theta_d). \tag{1}$$

To incorporate the covariate values for that document, a topic-prevalence vector θ_d is drawn from a logistic-normal distribution:

$$\theta_d|y_{d\gamma}, \Sigma \sim \text{LogisticNormal}(\mu = y_{d\gamma}\Sigma), \tag{2}$$

where $y_d\gamma$ lists the values of the metadata covariates for document d and γ relates these covariate values to the topic-prevalence.

Conditional in the topic chosen (z_{dn}), a specific word w_{dn}, is selected from the overall corpus vocabulary V, using the following process:

$$w_{dn}|z_{dn}, \phi_{dkv} \sim \text{Multinomial}(\phi_{dk1}, ..., \phi_{dkV}), \tag{3}$$

where the word probability ϕ_{dkv} is parameterized in terms of log-transformed rate deviations from the rates of a corpus-wide background distribution m_v (ibid.). The log-transformed rate deviations can then be specified by a collection of parameters $\{\boldsymbol{\kappa}\}$, where $\kappa^{(t)}$ is a K-by-V matrix containing the log-transformed rate deviations for each topic k and term v, over the baseline log-transformed rate for term v. This matrix is the same for all A levels of covariates. To put it differently, $\kappa^{(t)}$ indicates the importance of the term v given topic k regardless of the covariates. Similarly, $\kappa^{(c)}$ is a A-by-V matrix, indicating the importance of the term v given the covariate level c regardless of the topic. Finally, $\kappa^{(i)}$ is a A-by-K-by-V matrix, collecting the covariate-topic effects:

$$\phi_{dkv}|z_{dn} = \frac{\exp(m_v + \kappa^{(t)}_{kv}, \kappa^{(c)}_{y_d v} + \kappa^{(i)}_{y_d kv})}{\sum_v \exp(m_v + \kappa^{(t)}_{kv}, \kappa^{(c)}_{y_d v} + \kappa^{(i)}_{y_d kv})}. \tag{4}$$

The STM maximizes the posterior likelihood that the observed data were generated by the above data-generating process using an iterative approximation-based variational expectation-maximization algorithm[11] available in R's stm package (M. Roberts, B. Stewart, and Tingley, 2016b).

This process generates two posterior distribution parameters:

1. ϕ is a K-by-V matrix (where K = number of topics and V = vocabulary or unique terms), where the entry ϕ_{kvc} can be interpreted as the probability of observing the v-th word in topic k for the covariate level c (the news website).

[11] A technical description of this maximization process can be found in M. E. Roberts, B. M. Stewart, and E. M. Airoldi (2016)

2. θ is a D-by-V matrix (where D = number of documents and V = vocabulary or unique terms) of the document-topic distributions, where the entry θ_{dk} can be interpreted as the proportion of words in document d which arise from topic k, or rather as the probability that document d deals about topic k.

In section 5.1 the posterior distribution θ is used to estimate the conditional expectation of topic prevalence for given document characteristics. In order to calculate the sentiment value in section 5.2 each document d is assigned to the topic with the highest probability ($\max(\theta_k)$ for each document d).

4.2 Model and parameter selection

Inference of mixed-membership models, such as the one applied in this paper, has been a thread of research in applied statistics in the past few years (Blei et al. (2003) Erosheva et al. (2004) Braun and McAuliffe (2010)). Topic models are usually imprecise as the function to be optimized has multiple modes, such that the model results can be sensitive to the starting values (e.g. the number of topics). Since an ex ante valuation of a model is hardly possible, I compute a variety of different models and compare their posterior probability. This enables me to check how results vary for different model solution (M. Roberts, B. Stewart, and Tingley, 2016a). I then cross-checked some subset of assigned topic distributions to evaluate whether the estimates align with the concept of interest (Gentzkow et al., 2017). These manual audits are applied together with numeric optimization based on the topic coherence measure suggested by Mimno et al. (2011).

This process revealed that a model with 50 topics best reflects the structure in the corpus. Furthermore, the news website of a document (article) is used as covariates in the topic prevalence. In other words, the corresponding news website of an article influences the probability distribution of topics for that document.

5 Empirical Evaluation

This section summarizes the results of the STM. Subsequently "the two T's" (Topic and Tone) of the corpus are analyzed according to the following approaches: (1) The document-topic probability θ_{dk} is used to estimate the conditional expectation of topic prevalence for given document characteristics (section 5.1). A set of topics is selected, that most distinctly discuss a particular party or a topic related to the federal elections. (2) Articles that are assigned to the selected topics with the highest probability are then used to conduct a dictionary-based sentiment analysis (section 5.2). In order to check whether the sentiment values of certain topics are correlated with the results of voting preferences, the cross correlation function between these two concepts is calculated in 5.3.

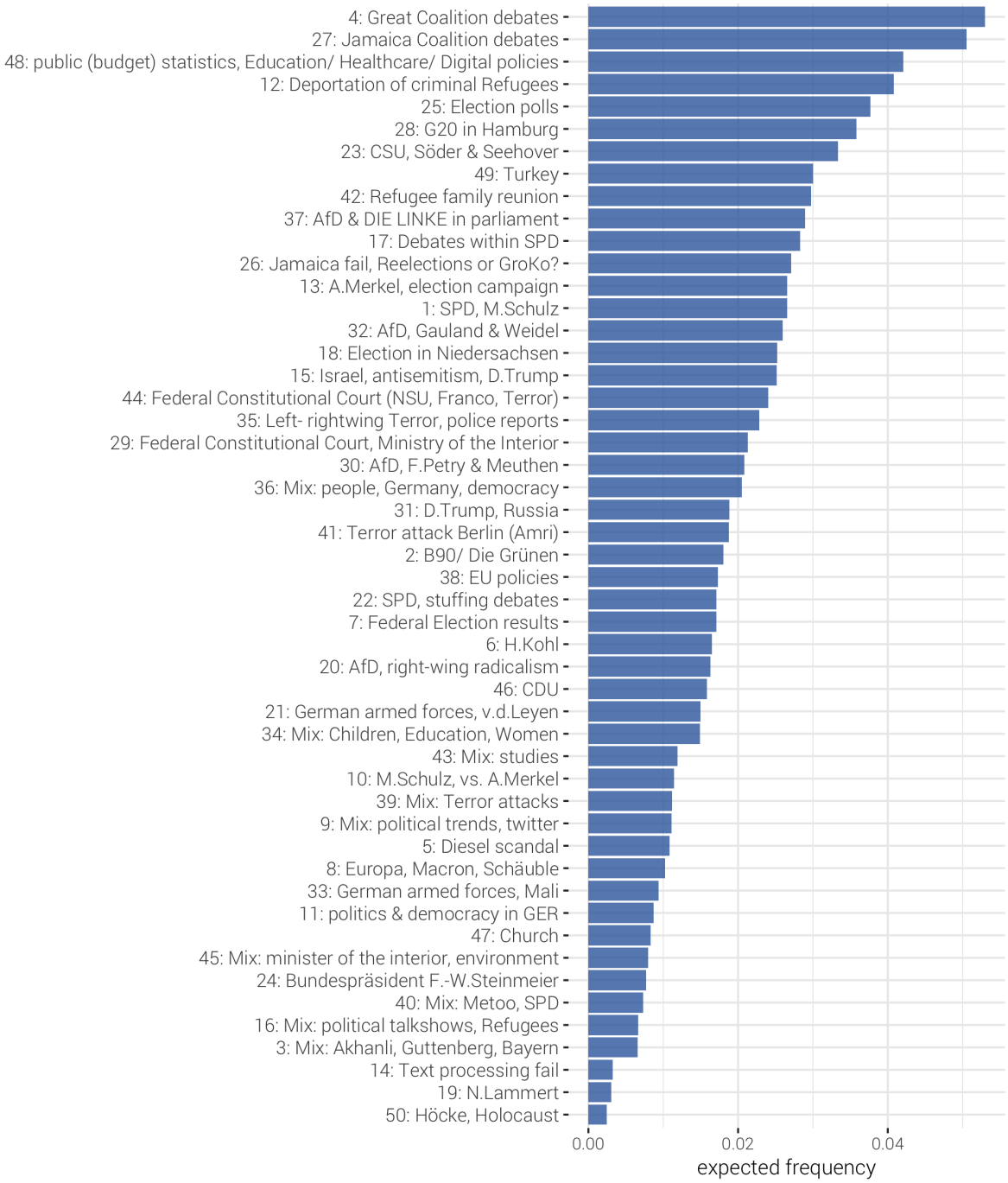
5.1 Topic

In order to get an initial overview of the results, Figure 6 displays the topics ordered by their expected frequency across the corpus. To assign a label to each topic, I looked at the most frequent words in that topic and the most representative articles (M. E. Roberts, B. M. Stewart, and E. M. Airoldi, 2016).

It becomes apparent that topic 4 about the coalition talks between CDU/CSU and SPD - the "Grand coalition" or "GroKo" - is the topic with the highest expected frequency in the whole corpus, followed by the topic about the so-called Jamaica parties (CDU/CSU,

FDP and B90/Die Grünen), which was the first alternative to be negotiated directly after the elections.

Figure 6: Expected topic proportion



The remaining analysis is limited to topics closely related to one or more parties. For this reason, the following topics were selected. The most frequent words of these topics at each news website can be seen in Appendix A.2:

1. Topic 1: About the SPD, mainly about the election campaign and Martin Schulz as candidate for the chancellor.

2. Topic 2: About B90/Die Grünen, mainly covering issues regarding the party's personell debates.

3. Topic 4: Covering the debates about the great coalition talks, mainly after the failure of the Jamaica coalition talks.

4. Topic 13: About Angela Merkel, mainly right before the election.

5. Topic 17: Covering votes within the SPD, mainly regarding the vote about a possible coalition with CDU/CSU ("GroKo").

6. Topic 20: About the AfD, mainly about their relation to right-wing extremist groups.

7. Topic 22: About SPD, mainly covering issues regarding the party's personell debates

8. Topic 23: About issues regarding the CSU, mainly about the competition between Horst Seehofer and Markus Söder and the negotiations with the CDU/CSU.

9. Topic 26: Discussing the failure of the Jamaica coalition talks and the two possible alternatives: Reelections or a great coalition.

10. Topic 27: Covering the Jamaica coalition talks, mainly focusing on the smaller players Bündnis B90/Die Grünen and FDP.

11. Topic 30: About the AfD, mainly about the resignation of Frauke Petry and Jörg Meuthen.

12. Topic 32: About the AfD, mainly about Alice Weidel and Alexander Gauland, voted as parliamentary party leaders after the resignation of Frauke Petry.

13. Topic 37: Covering debates of AfD and DIE LINKE in the parliament (Deutscher Bundestag).

14. Topic 46: Covering issues regarding the CDU/CSU.

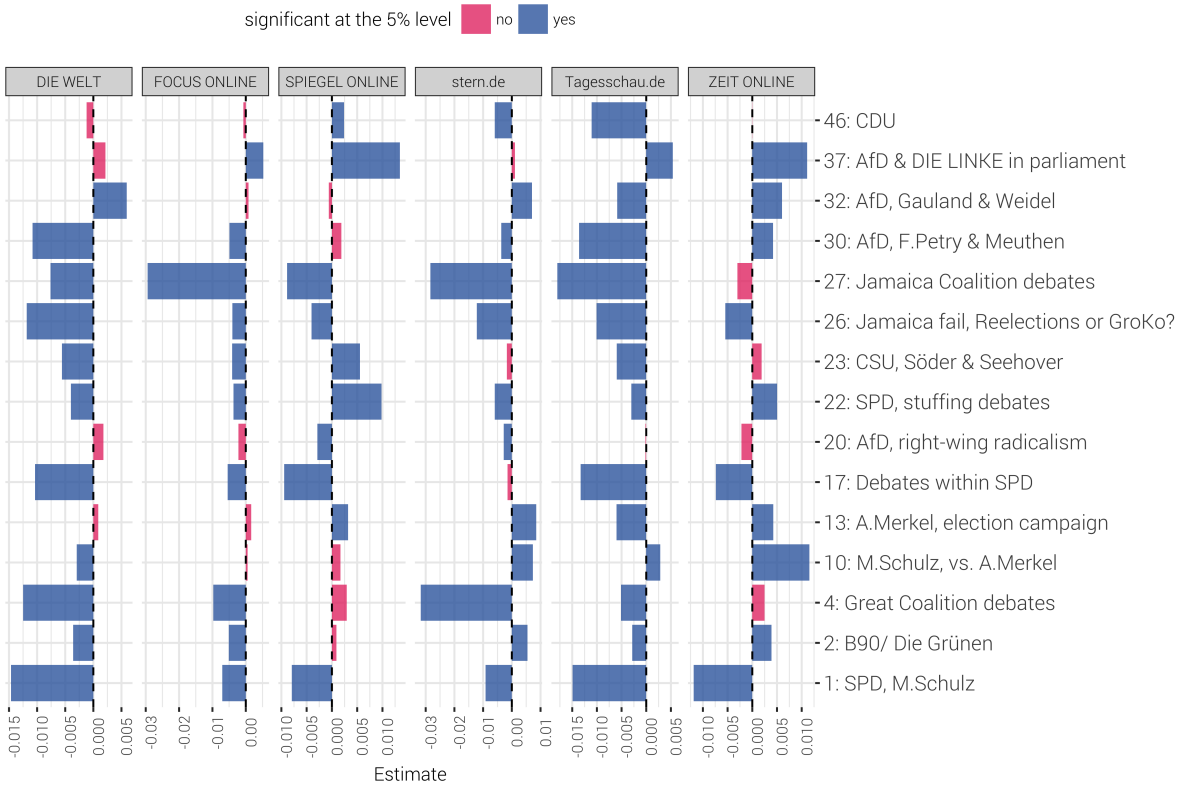
To estimate the differences of topic prevalence of the mentioned topics for the different websites, a linear model is estimated for each topic k, where the documents are observations, the dependent variable is the posterior probability of the respective topic (θ_d) and the covariates are dummy variables that are 1 if the document was published by the respective website and 0 otherwise (see equation 5). To incorporate uncertainty in the dependent variable, a set of topic proportions are drawn from the variational posterior (the unnormalized topic proportions) repeatedly. Then, the coefficients are computed as the average over all results (M. E. Roberts, B. M. Stewart, and E. M. Airoldi, 2016).

$$\begin{aligned}\theta_d = \beta_0 + \beta_1 x_{\text{FOCUS ONLINE,d}} + \beta_2 x_{\text{SPIEGEL ONLINE,d}} + \\ \beta_3 x_{\text{stern.de,d}} + \beta_4 x_{\text{Tagesschau.de,d}} + \beta_5 x_{\text{DIE WELT,d}} + \\ \beta_6 x_{\text{ZEIT ONLINE,d}} + \epsilon\end{aligned} \tag{5}$$

Figure 7 shows the regression results for the topics selected above (see appendix A.3 for the result tables). The coefficients indicate the deviation from the base value of Bild.de. Starting from above it becomes apparent that the topic prevalence of topic 46 (regarding the CDU/CSU) is significantly less for Tagesschau.de and Stern.de and significantly more for SPIEGEL ONLINE. The other media do not show any significant difference to Bild.de

for this topic. The opposite is true for topic 37: With the exception of Stern.de and DIE WELT, topic prevalence for this topic is significantly higher for all media than for Bild.de. With the following two topics on AfD it is striking that the topic prevalence at Tagesschau.de is significantly lower compared to Bild.de. The topics concerning the Jamaican coalition (topic 27) and the failure (topic 26) seem to be discussed most likely at Bild.de. The case is different for the CSU issue (Topic 23), where SPIEGEL ONLINE has the highest probability. The same applies to the topic related to the personnel debates of the SPD (22). However, Bild.de has the highest topic prevalence for the topic related to votes within the SPD, especially the vote on the "GroKo" (17). The same applies to the topic regarding the SPD in general and Martin Schulz in particular (1). Overall, topics concerning the SPD seem to be more frequent at Bild.de than in the other media. Moreover, the distribution of topics at FOCUS ONLINE seems to be the most similar to that of Bild.de, while the biggest differences exist between Bild.de and Tagesschau.de.

Figure 7: Regression results



5.2 Tone

To conduct the sentiment analysis, those documents are selected for which one of the above topics has the highest posterior probability and if this probability is greater than 30%. A dictionary-based method is then applied to the remaining 5,611 documents with the aim to measure the tone (or sentiment) of a document. The idea of a sentiment analysis is to determine the attitude of a writer toward the overall tonality of a document. To conduct such an analysis, a lists of words (dictionary) associated with a given emotion, such as negativity is pre-defined by the analyst. The document is then deconstructed into individual words and the frequencies of words contained in a given dictionary are calculated.

Such lexical or "bag-of-words" approaches are widely presented in the finance literature to determine the effect of central banks' monetary policy communications on asset prices and real variables (Nyman et al. (2018) Tetlock (2007), Tetlock et al. (2008)). Hansen and McMahon (2016) use a similar approach to measure "the two Ts" (Topic and tone). They explore the effects of FOMC (Federal Open Market Committee) statements on both market and real economic variables. To understand the latent topic of a statement, they apply LDA on a corpus of 142 FOMC decision statements split into sentences. They then measure how the central bank is talking about that topic, using a dictionary approach. To calculate their score, they subtract the negative words from the positive words und divide this by the number of total words of the statement. A similar score is used by Nyman et al. (2018), who measure the effect of narratives and sentiment of financial market text-based data on developments in the financial system. They count the number of occurrences of excitement words and anxiety words and then scale these numbers by the total text size as measured by the number of characters.

The present paper uses a dictionary that lists words associated with positive and negative polarity weighted within the interval of $[-1; 1]$. SentimentWortschatz[12], is a publicly available German-language resource for sentiment analysis, opinion mining, etc.. The current version of SentiWS (v1.8b) contains 1,650 positive and 1,818 negative words, which sum up to 15,649 positive and 15,632 negative words including their inflections, respectively. Table 2 shows ten examples entries of the dictionary.

Table 2: Sentiment Dictionary (Sample)

	word	value
1	verachtung	-0.33
2	kriminalität	-0.00
3	eingehen	-0.00
4	oase	0.00
5	panne	-0.19
6	unregelmäßig	-0.00
7	hochattraktiv	0.00
8	zweideutig	-0.32
9	streß	-0.00
10	inkonsequenz	-0.05

The sentiment score for each document d is calculated based on the weighted polarity values for a word, defined on an interval between -1 and 1. The score is then calculated from the sum of the words in a document (which can be assigned to a word from the dictionary) divided by the total number of words in that document:

$$\text{SentScore}_d = \frac{|\text{positive polarity score}_d| - |\text{negative polarity score}_d|}{|\text{TotalWords}_d|} \tag{6}$$

The results of the analysis for each topic on a monthly basis are listed in table A.4, aggregated on all newspapers. Each sentiment value is weighted by the relative share of the topic in the overall reporting of that month.

Some conclusions can be drawn from this table. First of all, it can be seen that, on monthly average, all topics are discussed almost exclusively negatively. An exception is topic 27 concerning the Jamaica coalition negotiations, which shows a positive sentiment value for a short period of time (October 2017).[13]

[12]SentiWS for short. available here: http://wortschatz.uni-leipzig.de/de/download

[13]Topics 22 and 26 also show positive values in July 2017, but the number of observations is very low.

Figure 8 illustrates the values from the table normalized between 0 and 1. It becomes apparent that although topic 27 is the only one with a positive value, it also has the most negative value in the following month (November 2017), after it became clear that there would be no coalition between the CDU/CSU, FDP and Die Grünen. A similar trend can be observed for topic 26, which also includes the Jamaica Coalition: In November 2017, observations increase to 230 and the negative sentiment value rises sharply. Concerning the topic that discusses the great coalition between CDU/CSU and SPD (topic 4), it is evident that the overall tone in which this topic is discussed is generally decreasing from November 2017 to January 2018, but in the following February, the sentiment value of this topic rises. However, the sentiment score of topics that deal with the SPD (1, 17, 22) is diminishing in the course of time, with topic 17 recording the largest decline. For the other parties the process is rather zigzag-like. The figures shows no evidence for the reproach, that the mass media reports more negatively about the AfD.

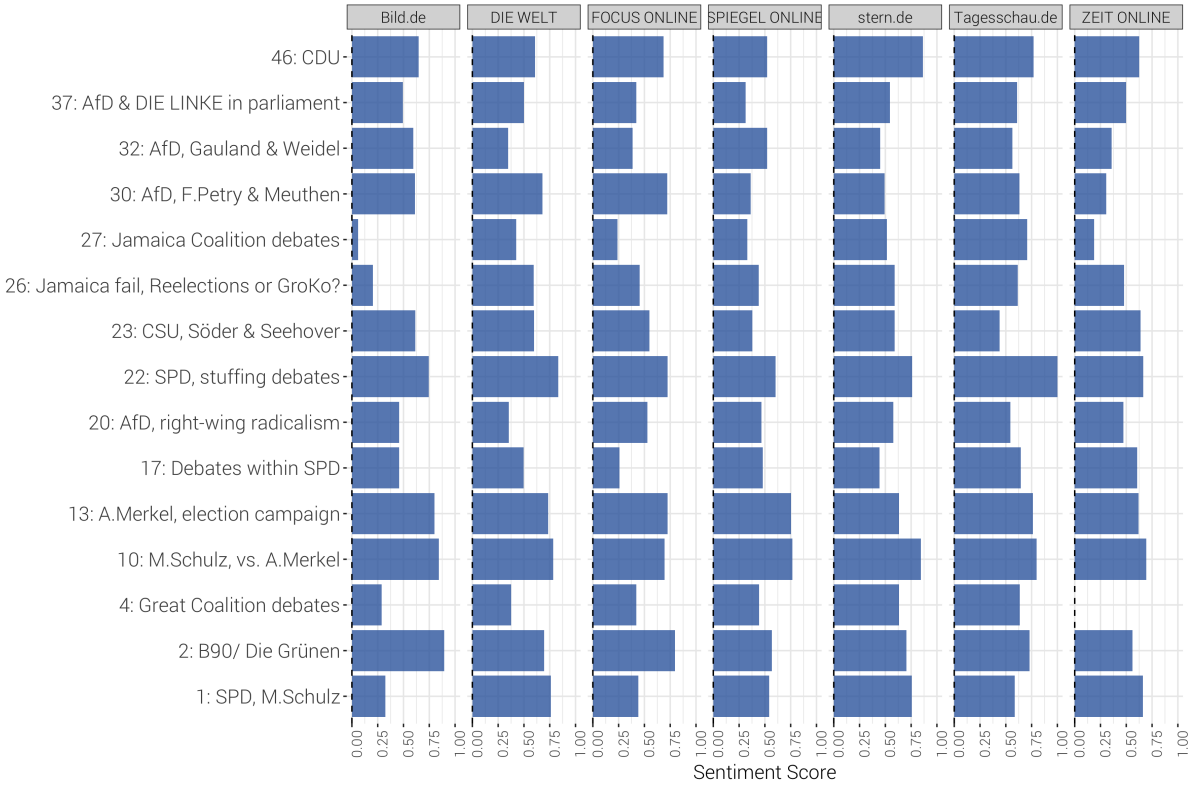
Figure 8: Monthly Sentiment Score

The sentiment value aggregated by news provider is listed in table A.5. Again, it becomes apparent, that all topics show a negative value. In order to analyze the differences between the news websites, two different figures are considered: (1) The bar plot is used to examine the polarity tendencies of the individual topics for a the respective website

(Figure 9) and (2) the radar plot is considered to observe the differences between the websites (Figure 10).

Starting with the bar plot it becomes apparent that topics that include the coalition negotiations (26, 27, 4) and the SPD (1, 17) are the most negative at Bild.de. The topics relating to AfD (20, 30, 32, 37) are also discussed more negatively. Looking at the values of DIE WELT, two of the AfD topics have the most negative values (32, 20). Topic 27 concerning the Jamaica Coalition and the Grand Coalition (4) also score relatively negatively. Concerning FOCUS ONLINE, it is mainly topics that relate to the SPD (27, 17, 4, 1) that have a strong negative sentiment value, together with topic 32 and 37 - both related to AfD. Turning to SPIEGEL ONLINE, it is noticeable that the difference in sentiment value between the individual topics is less pronounced. Topics 13 (election campaign of A.Merkel) and 10 (A.Merkel vs M.Schulz) stand out as comparatively less negative. However, these issues are also the least negatively discussed in the other media. Also at stern.de the difference in sentiment value is less significant and overall less negative. The topics regarding CDU/CSU (46) and Martin Schulz (10) score the most positively (or least negatively). Tagesschau.de is the least negative on most topics, or even once positive. However, this does not apply to topic 23 (CSU), where tagesschau.de is most negative in comparison to the other media. As with Bild.de, the issues relating to the coalition negotiations (27 and 4) also come off rather badly with ZEIT ONLINE. However, the issues surrounding AfD (30, 32, 37 and 20) are even more negative than at Bild.de.

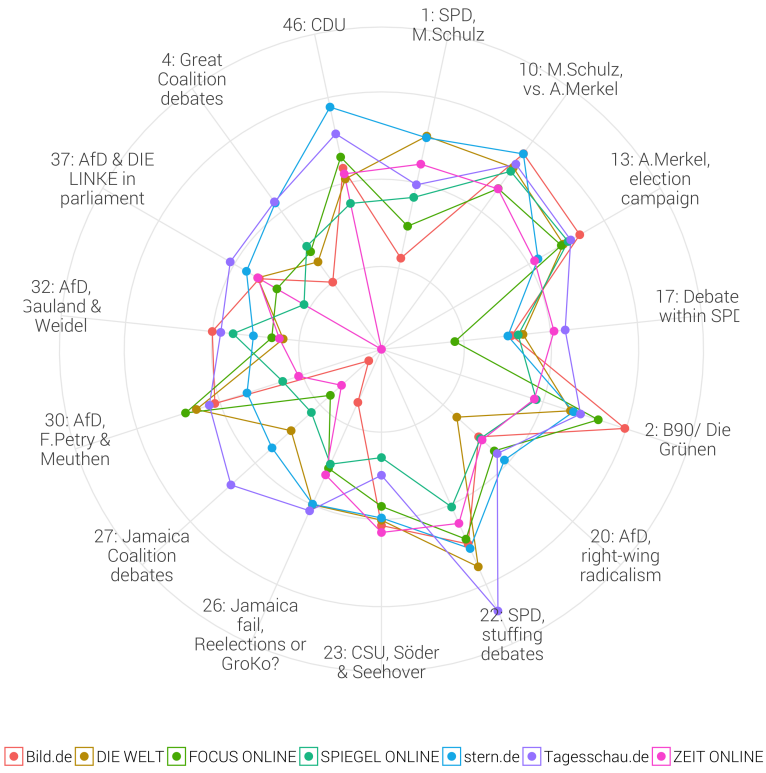
Figure 9: Sentiment Score by news website



A good overview of how differently the topics are discussed by the providers is shown in Figure 10. It becomes evident that the sentiment value of the media differs most notably with regard to topic 27 and topic 4, i.e. the topics on which the coalition negoti-

ations are reported. With regard to the Jamaica coalition, Bild.de reports the most and tagesschau.de the least negative. The reporting of ZEIT ONLINE concerning the grand coalition is the one with the most negative sentiment value and again Tagesschau.de, together with stern.de, the one with the value which is least negative. Furthermore, it becomes evident that the negative sentiment value of FOCUS ONLINE regarding topic 17 is high in relation to the other media. FOCUS ONLINE thus reports comparatively more negatively on the debates within the SPD. This includes in particular the vote on a possible coalition with CDU/CSU/CSU. For topic 1, which also deals with the SPD, the value of FOCUS ONLINE is rather negative, only undercut by Bild.de. Topics related to AfD do not show striking differences.

Figure 10: Radar Plot of Sentiment Scores



After the figures above have been analyzed, the following points can be summarized:

1. The sentiment value of the SPD is decreasing over time, especially regarding debates within the party (topic 17).

2. The topics relating to the coalition talks on Jamaica (26, 27) and the grand coalition (4) are discussed rather critically, but they also show the greatest differences between the media.

3. In contrast, the tonality of the topics in relation to the AfD shows rather small differences.

4. Overall, the sentiment value at Tagesschau.de is the least negative and only shows a comparatively strong negative value at topic 23, concerning the CSU.

5.3 News sentiment and poll data

This section seeks to examine the association between sentiment reflected in online news content and phone poll results in Germany. Specifically, it aims to find the extent to which online sentiment and phone survey results correlate given a number of lags. I use the data from the "Sonntagsumfrage" (Sunday survey) from infratest dimap.[14] The institution regularly asks at least 1000 German citizens the question: "Which party would you choose if federal elections were to take place next Sunday?" The survey thus measures the current election tendencies and therefore reflects an intermediate state in the opinion-forming process of the electoral population.

Much of the research on online content and political trends have focused on traditional weblogs and social media websites, such as Twitter, Facebook, MySpace, and YouTube. These studies have shown that social media is used to spread political opinions and that these considerations reflect the political landscape of the offline world. Tumasjan et al. (2010) investigate Tweets between August 13th and September 19th, 2009, prior to the German national elections to examine whether Twitter messages reflect the current offline political sentiment and whether it can be used to predict the popularity of parties or coalitions in the real world. With regard to the later question, they compare the share of attention the political parties receive on Twitter with the election result to examine whether the activity on Twitter can serve as a predictor of the election outcome. They found that the number of tweets reflects the election result and even comes close to traditional election polls.

Fu and Chan (2013) use a corpus of online posts from discussion forums and blogs to examine the extent to which online sentiment reflected in social media content can predict phone survey results in Hong Kong. They build a sentiment classifier conducting a support vector machine analysis on a training set of 2,000 manually labeled posts. In order to evaluate the temporal relationship between the time series of the online sentiment score and the results of the telephone survey, a cross correlation analysis was conducted, using the Box and Jenkins autoregressive integrated moving average (ARIMA) method (Box et al., 2008). Estimating the cross-correlation functions of the residuals, they find that online sentiment scores can lead phone survey results by about 8–15 days.

In a more recent conference paper, Padmaja et al. (2014) identify the scope of negation in news articles for two political parties in India (BJP and UPA) to analyze how the choice of certain words used in these texts influence the sentiments of public in polls. Comparing three different sentiment analysis methods (two machine learning and one dictionary method), they observe that the choice of certain words used in political text was influencing the sentiments in favor of BJP. They conclude that this sentiment bias might be one of the causes for the election results in 2014.

Dewenter et al. (2018) use human-coded data from leading media in Germany together with the German Politbarometer survey to investigate how media coverage affects short- and long-term political preferences between February 1998 and December 2012. They find a positive correlation between the media coverage and the short-term voting intention for a political party. In the long-term, however, voting preferences are stable.

In the present paper, the relationship between monthly average of both the sentiment value of individual topics (x_t) and the survey value of the parties (y_t) is estimated using the cross correlation function (CCF). Thus, the CCF between x_{t+h} and y_t for $h \pm 1$,$h \pm 2$,$h \pm 3$ is computed. A negative value for h is a correlation between the topic sentiment value at a time before t and the survey value at time t. The correlation value for $h = 0$ indicates the contemporary correlation between the two time series. Based on the coefficients of

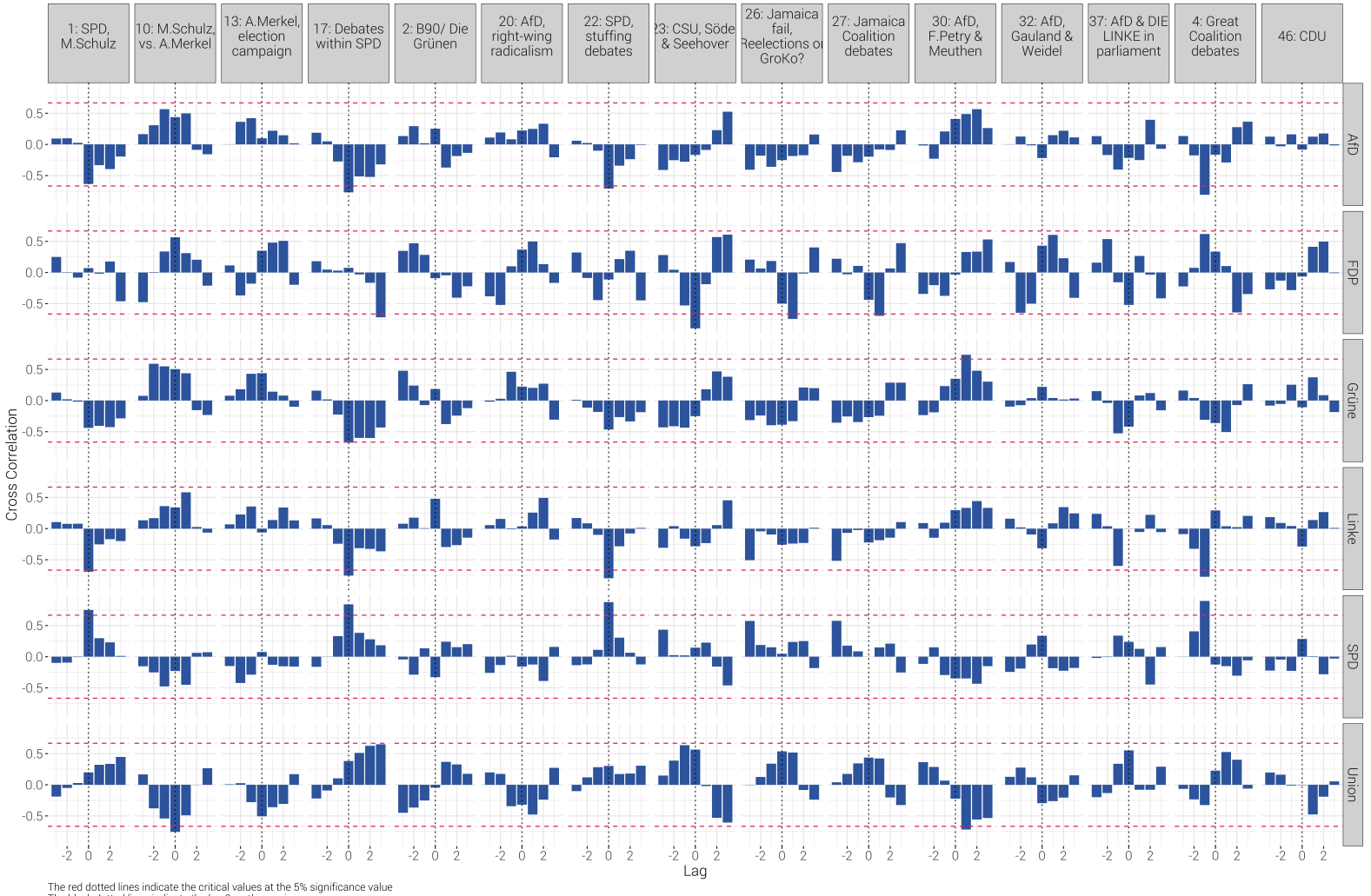
[14] https://www.infratest-dimap.de/umfragen-analysen/bundesweit/sonntagsfrage/

the cross correlation estimation shown in Figure 11, the significant correlations between topic sentiment and survey value are evaluated for each party.[15] It is important to note that no causal relationships are described below, but only the correlation between the two time series.

The survey results of the AfD correlate negatively with topics relating to the SPD (17, 22) at lag 0. Thus, if the SPD was more negatively reported, the poll value of the AfD increased in the same month (and vice versa). Another significant negative correlation exists between the reporting on the GroKo (4) and the survey value of AfD at lag -1 (x_{t-1}). So if the GroKo was more negatively reported in one month, the survey value of the AfD increased in the following month (and vice versa). For the FDP, too, only negative correlation coefficients can be detected, with the strongest negative correlation existing for the topic relating to the CSU (23). If the CSU got off worse in the online news, the poll value of the FDP went up. Another interesting observation is that the FDP's poll results correlate negatively with issues relating to the Jamaica coalition at lag 1 (x_{t+1}). So if the poll results for the FDP rose in one month, the following month the FDP was reported more negatively. The Green Party survey results show no negative correlation with any of the topics, except topic 30 at lag 1. It is striking that there seems to be a strong negative correlation between the SPD topics (1, 17, 22) and the poll results of the left party (DIE LINKE). This means that the poll value of the left party has climbed if the topics related to the SPD were discussed more negatively. Same applies to the reporting on the GroKo (30) for lag -1. Conversely, the SPD's survey results correlate strongly positively with these topics, and also with topic 30 with a delay of one month. For the CDU/CSU, too, only significant negative correlations are discernible: the survey results correlate negatively with the topic of the Schulz v Merkel debate (10) and negatively with topic 30 with a delay of one month (x_{t+1}).

[15] The value of the cross correlation coefficients for lag 0 are listed in the appendix A.6

Figure 11: Cross-Correlation Coefficients



The red dotted lines indicate the critical values at the 5% significance value
The black dotted lines indicate the lag 0 on the x-axis.

After the figures above have been analyzed, the following points can be summarized:

1. Only the survey results of the SPD correlate positively with the emotional value of the topics. There seems to be a strong correlation between the way topics concerning the SPD are discussed in the online news and the poll results.

2. The poll results of the Left Party, on the other hand, seem to correlate negatively with the reporting on the SPD.

3. Similar tendencies can also be seen with regard to the AfD, since here too the survey results correlate significantly negatively with the topics about the SPD and the grand coalition.

Summarizing the analyses from this and the previous section, it can be observed that the positive correlation between the emotional value of the reporting and the survey value of a party is particularly large if the reporting is conspicuously negative.

6 Conclusion

The ongoing discussion about the influence of digital media on the political opinion-forming process addresses the question whether there are convergence tendencies within the mass media and whether the reporting in the media correlates with the voting preferences. To analyze this question, this paper examines (1) whether the political reporting of different media differs in terms of topic frequency and topic tonality and (2) whether the emotional value of the reporting correlates with poll results.

Using text data of 14,937 online news articles from seven German news providers about domestic politics, I first estimate a Structural Topic Model to find the latent topics in the news articles in order to answer (1). After assigning a topic to each news article, the sentiment value of articles about contemporary political events is calculated using a dictionary-based method. In order to tackle (2), the results from the sentiment analysis are then compared to poll results.

Regarding (1), the analysis revealed that there are differences between the media considered, both in terms of topic prevalence and the way in which these topics are discussed. Although the topics are discussed negatively on average, differences can still be observed, especially regarding topics that deal with the coalition negotiations. The smallest differences were observed for topics concerning the AfD. However, no evidence has been found that the media systematically report more negatively on the AfD than on other parties. With regard to (2), the analysis has shown that the tonality of topics discussed by the SPD shows a strong positive correlation to current survey results. Overall, there seems to be a link between reporting on political issues and electoral preferences. The results of this study show evidence that the content of media could have an influence on the opinion-forming process of the voters and therefore underline the responsibility of media in the political context.

References

Baturo, Alexander, Niheer Dasandi, and Slava J. Mikhaylov (Aug. 2017). "What Drives the International Development Agenda? An NLP Analysis of the United Nations General Debate 1970-2016". In: *arXiv:1708.05873 [cs]*. arXiv: 1708.05873. URL: http://arxiv.org/abs/1708.05873.

Bholat, David M. et al. (June 2015). "Text Mining for Central Banks". In: *SSRN Electronic Journal*. URL: http://www.academia.edu/13430482/Text_mining_for_central_banks (visited on 11/06/2017).

Blei, David M. (Apr. 2012). "Probabilistic Topic Models". In: *Commun. ACM* 55.4, pp. 77–84. URL: http://doi.acm.org/10.1145/2133806.2133826.

Blei, David M., Andrew Y Ng, and Michael I Jordan (Jan. 2003). "Latent dirichlet allocation". In: *Journal of machine Learning research* 3, pp. 993–1022.

Box, George E. P., Gwilym M. Jenkins, and Gregory C. Reinsel (2008). *Time series analysis: forecasting and control*. 4th ed. Wiley series in probability and statistics. Hoboken, NJ: Wiley.

Braun, Michael and Jon McAuliffe (Mar. 2010). "Variational inference for large-scale models of discrete choice". In: *Journal of the American Statistical Association* 105.489. arXiv: 0712.2526, pp. 324–335. URL: http://arxiv.org/abs/0712.2526 (visited on 01/19/2018).

Dewenter, Ralf, Melissa Linder, and Tobias Thomas (Apr. 2018). "Can Media Drive the Electorate? The Impact of Media Coverage on Party Affiliation and Voting Intentions". In: *Working Paper Series, Helmut Schmidt University Hamburg, Department of Economics* 179.

Erosheva, Elena, Stephen Fienberg, and John Lafferty (June 2004). "Mixed-membership models of scientific publications". en. In: *Proceedings of the National Academy of Sciences* 101.suppl 1, pp. 5220–5227. URL: http://www.pnas.org/content/101/suppl_1/5220 (visited on 10/12/2017).

Farrell, Justin (May 2016). "Corporate funding and ideological polarization about climate change". en. In: *Proceedings of the National Academy of Sciences* 113.1, pp. 92–97. URL: http://www.pnas.org/content/113/1/92 (visited on 11/09/2017).

Fu, King-wa and Chee-hon Chan (Sept. 2013). "Analyzing Online Sentiment to Predict Telephone Poll Results". en. In: *Cyberpsychology, Behavior, and Social Networking* 16.9, pp. 702–707. URL: http://online.liebertpub.com/doi/abs/10.1089/cyber.2012.0375 (visited on 03/19/2018).

Gentzkow, Matthew, Bryan T. Kelly, and Matt Taddy (Mar. 2017). *Text as Data*. Working Paper 23276. National Bureau of Economic Research. URL: http://www.nber.org/papers/w23276.

Griffiths, Thomas L. and Mark Steyvers (Jan. 2002). "A probabilistic approach to semantic representation". In: *Proceedings of the Annual Meeting of the Cognitive Science Society* 24.24. URL: https://escholarship.org/uc/item/44x9v7m7 (visited on 11/16/2017).

— (June 2004). "Finding scientific topics". en. In: *Proceedings of the National Academy of Sciences* 101.suppl 1, pp. 5228–5235. URL: http://www.pnas.org/content/101/suppl_1/5228 (visited on 10/12/2017).

Grimmer, Justin and Brandon Stewart (2013). "Text as Data: The Promise and Pitfalls of Automatic Content Analysis Methods for Political Texts". In: *Political Analysis* 21, pp. 267–297.

Hansen, Stephen and Michael McMahon (Mar. 2016). "Shocking language: Understanding the macroeconomic effects of central bank communication". In: *Journal of*

International Economics. 38th Annual NBER International Seminar on Macroeconomics 99, S114–S133. URL: http://www.sciencedirect.com/science/article/pii/S0022199615001828 (visited on 03/07/2018).

HOFMANN, Thomas (1999). "Probabilistic Latent Semantic Indexing". In: *Proceedings of the 22Nd Annual International ACM SIGIR Conference on Research and Development in Information Retrieval*. SIGIR '99. New York, NY, USA: ACM, pp. 50–57. URL: http://doi.acm.org/10.1145/312624.312649.

MIMNO, David et al. (2011). "Optimizing Semantic Coherence in Topic Models". In: *Proceedings of the Conference on Empirical Methods in Natural Language Processing*. EMNLP '11. Stroudsburg, PA, USA: Association for Computational Linguistics, pp. 262–272. URL: http://dl.acm.org/citation.cfm?id=2145432.2145462.

MISHLER, Alan et al. (Aug. 2015). "Using Structural Topic Modeling to Detect Events and Cluster Twitter Users in the Ukrainian Crisis". en. In: *HCI International 2015 - Posters' Extended Abstracts*. Communications in Computer and Information Science. Springer, Cham, pp. 639–644. URL: https://link.springer.com/chapter/10.1007/978-3-319-21380-4_108 (visited on 10/12/2017).

MUELLER, Hannes Felix and Christopher RAUH (Sept. 2016). *Reading between the Lines: Prediction of Political Violence Using Newspaper Text*. SSRN Scholarly Paper ID 2843535. Rochester, NY: Social Science Research Network. URL: https://papers.ssrn.com/abstract=2843535 (visited on 11/09/2017).

NYMAN, Rickard et al. (Jan. 2018). "News and narratives in financial systems: exploiting big data for systemic risk assessment | Bank of England". In: *Bank of England Working Paper* 704. URL: https://www.bankofengland.co.uk/working-paper/2018/news-and-narratives-in-financial-systems (visited on 02/21/2018).

PADMAJA, S., Prof S. Sameen FATIMA, and Sasidhar BANDU (2014). "Evaluating Sentiment Analysis Methods and Identifying Scope of Negation in Newspaper Articles". en. In: *International Journal of Advanced Research in Artificial Intelligence (IJARAI)* 3.11. URL: http://thesai.org/Publications/ViewPaper?Volume=3&Issue=11&Code=IJARAI&SerialNo=1 (visited on 03/19/2018).

PAUL, Michael (2009). "Cross-Collection Topic Models: Automatically Comparing and Contrasting Text". MA thesis. University of Illinois at Urbana-Champaign.

PRITCHARD, J. K., M. STEPHENS, and P. DONNELLY (June 2000). "Inference of population structure using multilocus genotype data". eng. In: *Genetics* 155.2, pp. 945–959.

ROBERTS, Margaret E., Brandon M. STEWART, and Edoardo M. AIROLDI (July 2016). "A Model of Text for Experimentation in the Social Sciences". In: *Journal of the American Statistical Association* 111.515, pp. 988–1003. URL: http://dx.doi.org/10.1080/01621459.2016.1141684.

ROBERTS, Margaret E., Brandon M. STEWART, Dustin TINGLEY, et al. (Oct. 2014). "Structural Topic Models for Open-Ended Survey Responses". en. In: *American Journal of Political Science* 58.4, pp. 1064–1082. URL: http://onlinelibrary.wiley.com/doi/10.1111/ajps.12103/abstract.

ROBERTS, Margaret, Brandon STEWART, and Dustin TINGLEY (2016a). "Navigating the Local Modes of Big Data: The Case of Topic Models." In: *Computational Social Science: Discovery and Prediction*. New York: Cambridge University Press.

— (Jan. 2016b). "stm: R Package for Structural Topic Models". In: *Journal of Statistical Software* forthcoming.

ROBERTS, Margaret, Brandon STEWART, Dustin TINGLEY, and Edoardo AIROLDI (2013). "The Structural Topic Model and Applied Social Science". In: *Advances in Neural In-*

formation Processing Systems Workshop on Topic Models: Computation, Application, and Evaluation.

TETLOCK, Paul C. (June 2007). "Giving Content to Investor Sentiment: The Role of Media in the Stock Market". en. In: *The Journal of Finance* 62.3, pp. 1139–1168. URL: http://onlinelibrary.wiley.com/doi/10.1111/j.1540-6261.2007.01232.x/abstract.

TETLOCK, Paul C., Maytal SAAR-TSECHANSKY, and Sofus MACSKASSY (June 2008). "More Than Words: Quantifying Language to Measure Firms' Fundamentals". en. In: *The Journal of Finance* 63.3, pp. 1437–1467. URL: http://onlinelibrary.wiley.com/doi/10.1111/j.1540-6261.2008.01362.x/abstract (visited on 03/07/2018).

TUMASJAN, Andranik et al. (2010). "Predicting Elections with Twitter: What 140 Characters Reveal about Political Sentiment". en. In: *Proceedings of the Fourth International Conference on Weblogs and Social Media*. Washington. URL: https://www.researchgate.net/publication/215776042_Predicting_Elections_with_Twitter_What_140_Characters_Reveal_about_Political_Sentiment (visited on 03/17/2018).

WIEDMANN, Gregor (2016). *Text Mining for Qualitative Data Analysis in the Social Sciences*. 1st ed. Wiesbaden: VS Verlag für Sozialwissenschaften. URL: //www.springer.com/de/book/9783658153083 (visited on 11/26/2017).

A Appendices

A.1 Wordclouds

(a) DIE WELT

(b) FOCUS ONLINE

(c) SPIEGEL ONLINE

(d) Stern.de

(e) ZEIT ONLINE

A.2 Most frequent words

Topic: 1

Bild.de : schulz spd martin gabriel partei merkel chef kanzlerkandidat wahlkampf bundestagswahl wahl sigmar angela politik andrea

focus.de : schulz spd martin partei wahlkampf merkel kanzlerkandidat schröder politik bundestagswahl wahl chef scholz tv angela

spiegel.de : schulz spd martin kanzlerkandidat duell wahlkampf partei tv bundestagswahl merkel politik wahl sozialdemokraten umfragen chef

stern.de : schulz spd martin duell tv merkel kanzlerkandidat wahlkampf angela septemb bundestagswahl berlin partei herausforder wahl

tagesschau.de : schulz spd partei martin chef parteitag parteichef merkel scholz kanzlerkandidat genossen opposit groko juso müsse

welt.de : schulz spd martin gabriel kanzlerkandidat wahlkampf partei merkel welt bundestagswahl wahl sozialdemokraten berlin außenminist duell

zeit.de : schulz spd martin partei wahlkampf kanzlerkandidat genossen merkel berlin marcu chef glahn scholz bundestagswahl sozialdemokraten

Topic: 2

Bild.de : grünen özdemir göring eckardt partei habeck wagenknecht cem wahlkampf parteitag lilli linken katrin grüne link

focus.de : grünen özdemir grüne partei habeck göring eckardt cem parteitag linken robert flügel berlin realo katrin

spiegel.de : grünen özdemir habeck göring eckardt partei grüne parteitag katrin cem baerbock robert linken link flügel

stern.de : grünen özdemir grüne göring link eckardt partei cem parteitag linken rot habeck bundestagswahl wagenknecht katrin

tagesschau.de : grünen habeck partei özdemir top göring grüne wagenknecht eckardt parteitag baerbock linken flop cem linkspartei

welt.de : grünen özdemir habeck partei linken göring eckardt rot grüne robert cem link parteitag grün katrin

zeit.de : grünen özdemir partei linken link göring habeck eckardt parteitag grüne cem hofreit katrin realo baerbock

Topic: 4

Bild.de : spd union groko cdu csu koalit schulz koalitionsverhandlungen chef parteitag gespräch verhandlungen große großen martin

focus.de : spd union groko cdu koalit csu koalitionsverhandlungen schulz parteitag große verhandlungen chef großen sondierungen koalitionsvertrag

spiegel.de : spd union cdu csu koalit groko koalitionsverhandlungen schulz parteitag verhandlungen politik großen sondierungen chef sozialdemokraten

stern.de : spd union cdu csu verhandlungen koalit koalitionsverhandlungen schulz sondierungen groko berlin großen martin gespräch chef

tagesschau.de : spd union cdu csu koalitionsverhandlungen koalit groko schulz verhandlungen chef sondierungen parteitag gespräch großen große

welt.de : spd union koalit cdu csu groko koalitionsverhandlungen große schulz welt großen gespräch sondierungen verhandlungen chef

zeit.de : spd union koalit cdu csu große koalitionsverhandlungen schulz großen parteitag verhandlungen chef koalitionsvertrag sondierungen gespräch

Topic: 10

Bild.de : schulz spd merkel martin duell kanzlerin deutschland tv thema flüchtling kanzlerkandidat angela rent wahlkampf zitat

focus.de : schulz spd thema duell merkel tv martin wahlkampf deutschland kanzlerkandidat kanzlerin herausforder flüchtling angriff frage

spiegel.de : schulz spd martin merkel eu kanzlerkandidat deutschland europa duell thema italien kanzlerin tv flüchtlingskris maut

stern.de : schulz spd merkel martin kanzlerkandidat deutschland flüchtlingskris italien kanzlerin europa bildung union thema eu angela

tagesschau.de : schulz duell tv spd merkel thema siemen martin deutschland rent kanzlerkandidat herausforder maut menschen flüchtling

welt.de : schulz spd merkel martin duell deutschland thema tv flüchtling kanzlerkandidat cdu land welt stimmt kanzlerin

zeit.de : schulz spd duell merkel martin tv kanzlerkandidat deutschland angela kanzlerin thema wahlkampf flüchtling eu themen

Topic: 13

Bild.de : merkel kanzlerin angela cdu bundeskanzlerin union wahlkampf deutschland rede auftritt jahr politik bundestagswahl kanzleramt frage

focus.de : merkel kanzlerin angela cdu bundeskanzlerin union deutschland thema frage wahlkampf menschen wahl jahr bundestagswahl abstimmung

spiegel.de : merkel kanzlerin angela cdu bundeskanzlerin wahlkampf union chefin auftritt deutschland sebastian frage kanzleramt jahr zdf

stern.de : merkel angela kanzlerin cdu bundeskanzlerin union wahlkampf deutschland abstimmung bundestagswahl menschen thema frage jahr septemb

tagesschau.de : merkel kanzlerin angela cdu bundeskanzlerin thema chefin wahlkampf union abstimmung jahr deutschland kanzleramt brigitt forderung

welt.de : merkel angela kanzlerin cdu bundeskanzlerin deutschland union zdf duell wahlkampf tv welt regierung jahr frage

zeit.de : merkel angela kanzlerin cdu bundeskanzlerin wahlkampf union deutschland thema kritik frage menschen jahr jahren bundestagswahl

Topic: 17

Bild.de : spd schulz nahl groko gabriel partei chef koalit juso kühnert mitglied martin außenminist kevin große

focus.de : spd gabriel schulz außenminist partei sigmar juso koalit groko kühnert chef großen große union martin

spiegel.de : spd gabriel schulz partei mitglied außenminist koalit sigmar politik groko chef juso martin koalitionsvertrag sozialdemokraten

stern.de : spd schulz gabriel koalit partei groko martin union chef große juso parteitag sigmar großen außenminist

tagesschau.de : spd gabriel schulz partei koalit außenminist groko koalitionsvertrag chef großen martin große sigmar europa union

welt.de : spd schulz gabriel partei welt koalit nahl mitglied groko juso koalitionsvertrag sigmar außenminist martin kühnert

zeit.de : spd gabriel partei schulz sigmar koalit außenminist klingbeil martin union große großen parteitag juso sozialdemokrati

Topic: 20

Bild.de : afd storch twitter facebook account plakat tweet partei politik beatrix maier schrieb amann wahlbetrug post

focus.de : afd tweet twitter facebook partei politik vw aktion schrieb storch montag gruppen jahr arpp vorwürf

spiegel.de : afd vw hampel politik partei staatsanwaltschaft storch arpp rede volkswagen regierungserklärung konzern berlin vorwürf tweet

stern.de : afd vw facebook partei gruppen post hampel nrw storch antifa land berlin septemb landesverband niedersächsischen

tagesschau.de : afd account vw ndr twitter hampel fake arpp roth zitat partei suhren falsch ministerpräsid tweet

welt.de : afd hampel pegida politik welt partei landesverband plakat landesvorstand parteitag niedersachsen niedersächsischen storch mecklenburg vorpommern

zeit.de : afd jahr beruf funktion früher mitgli partei unbekannt arpp orientierung nationalkonservativ berlin sachsen landesverband identitären

Topic: 23

Bild.de : csu seehof söder horst bayern cdu chef union herrmann marku parteichef partei berlin ministerpräsid obergrenz

focus.de : csu seehof söder horst obergrenz union cdu partei bayern chef berlin ministerpräsid bundestagswahl marku parteichef

spiegel.de : csu seehof söder horst cdu obergrenz union bayern partei berlin chef bundestagswahl ministerpräsid marku politik

stern.de : csu seehof horst union cdu bundestagswahl obergrenz söder berlin chef bayern jamaika dobrindt partei ministerpräsid

tagesschau.de : csu seehof söder obergrenz horst union partei cdu berlin bundestagswahl chef bayern ministerpräsid marku bayerisch

welt.de : csu seehof söder bayern horst cdu union obergrenz herrmann partei chef marku berlin bundestagswahl ministerpräsid

zeit.de : csu seehof obergrenz söder horst cdu union bayern chef partei ministerpräsid bundestagswahl bayerisch herrmann dobrindt

Topic: 26

Bild.de : spd merkel jamaika neuwahlen koalit groko minderheitsregierung regierung bundestag schulz kanzlerin angela union scheitern parteien

focus.de : koalit spd neuwahlen jamaika merkel große minderheitsregierung steinmeier union regierung groko schulz scheitern bundespräsid großen

spiegel.de : koalit spd jamaika merkel neuwahlen minderheitsregierung große gespräch steinmeier union regierung schulz scheitern sozialdemokraten bundespräsid

stern.de : spd koalit merkel minderheitsregierung jamaika neuwahlen steinmeier große regierungsbildung union regierung großen schulz gespräch angela

tagesschau.de : koalit spd jamaika merkel minderheitsregierung neuwahlen gespräch große steinmeier regierungsbildung großen union scheitern bundespräsid schulz

welt.de : spd koalit jamaika neuwahlen merkel minderheitsregierung scheitern große gespräch steinmeier regierung union schulz sondierungen neuwahl

zeit.de : koalit spd merkel minderheitsregierung jamaika große scheitern regierung neuwahlen union gespräch großen schulz neuwahl regierungsbildung

Topic: 27

Bild.de : fdp grünen jamaika lindner csu cdu union grüne chef koalit parteien christian verhandlungen kubicki sondierungen

focus.de : fdp jamaika grünen lindner csu union cdu christian chef parteien grüne kubicki sondierungen verhandlungen liberalen

spiegel.de : fdp grünen lindner jamaika csu cdu union sondierungen grüne chef parteien christian politik koalit kubicki

stern.de : fdp jamaika grünen lindner csu cdu sondierungen scheitern koalit union parteien gespräch christian grüne chef

tagesschau.de : fdp grünen jamaika csu lindner union cdu parteien sondierungen grüne koalit chef verhandlungen gespräch themen

welt.de : fdp grünen jamaika lindner csu cdu welt sondierungen union grüne christian gespräch parteien kubicki chef

zeit.de : fdp grünen jamaika lindner csu union cdu grüne parteien koalit christian sondierungen chef gespräch kubicki

Topic: 30

Bild.de : afd petri partei meuthen frauk gauland fraktion weidel höcke bundestag bundesvorstand abgeordnet jörg parteitag co

focus.de : afd petri partei frauk fraktion meuthen höcke landtag immunität sachsen gauland bundestag pretzel austritt flügel

spiegel.de : afd petri partei frauk meuthen fraktion gauland pretzel bundestag sachsen landtag politik bundestagswahl höcke weidel

stern.de : afd petri frauk partei fraktion gauland meuthen bundestag pretzel weidel bundestagswahl landtag höcke alexand dresden

tagesschau.de : afd petri partei landtag frauk sachsen fraktion meuthen gauland bundestag höcke staatsanwaltschaft pegida dresden weidel

welt.de : afd petri partei bundestagswahl bundestag berlin cdu frauk wahl fraktion meuthen ergebni gauland direktmandat parlament

zeit.de : afd petri partei frauk fraktion gauland meuthen landtag bundestag parteitag höcke sachsen weidel septemb maier

Topic: 32

Bild.de : afd gauland weidel alic partei alexand deutschland spitzenkandidatin politik sayn özoguz pazderski spitzenkandidat zeitung land

focus.de : afd weidel gauland partei politik alexand alic deutschland sendung zdf moderatorin islam studio illner parteien

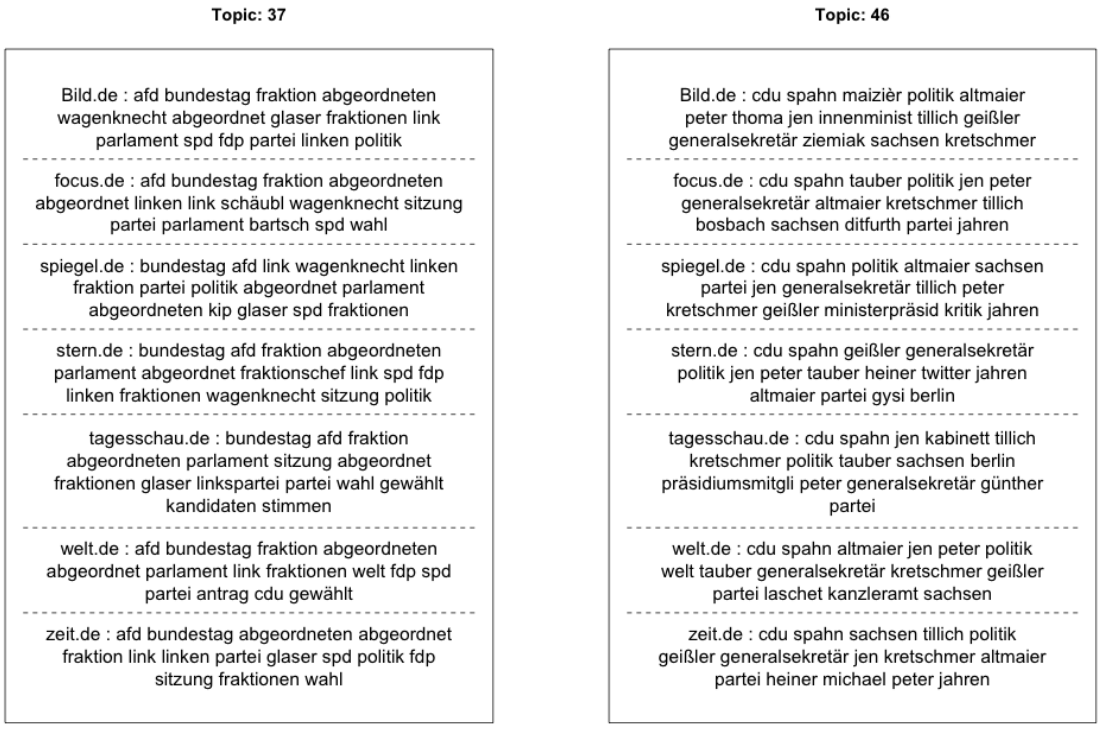
spiegel.de : afd gauland weidel partei özoguz politik alexand deutsch alic deutschland rechtspopulisten stiftung land rede höcke

stern.de : afd gauland weidel partei alic alexand deutschland özoguz höcke deutschen spitzenkandidat deutsch septemb spitzenkandidatin politikerin

tagesschau.de : afd gauland weidel partei stiftung meuthen alic deutschland alexand parteitag flügel höcke politik facebook kandidaten

welt.de : afd gauland weidel partei alic welt höcke alexand deutschland politik özoguz meuthen parteitag bundestag stiftung

zeit.de : afd gauland weidel partei höcke alexand deutschland özoğuz alic altern politik äußerungen deutschen nazi stiftung



A.3 Regression Results

topic_name	parameter	Estimate	Std. Error	t value	p
1: SPD, M.Schulz	(Intercept)	0.036	0.003	11.460	0.000
1: SPD, M.Schulz	FOCUS ONLINE	-0.007	0.004	-1.777	0.076
1: SPD, M.Schulz	SPIEGEL ONLINE	-0.008	0.004	-1.965	0.049
1: SPD, M.Schulz	stern.de	-0.009	0.004	-2.340	0.019
1: SPD, M.Schulz	Tagesschau.de	-0.015	0.005	-3.311	0.001
1: SPD, M.Schulz	DIE WELT	-0.015	0.004	-3.834	0.000
1: SPD, M.Schulz	ZEIT ONLINE	-0.012	0.004	-2.686	0.007
2: B90/ Die Grünen	(Intercept)	0.018	0.003	7.057	0.000
2: B90/ Die Grünen	FOCUS ONLINE	-0.005	0.003	-1.515	0.130
2: B90/ Die Grünen	SPIEGEL ONLINE	0.001	0.003	0.260	0.795
2: B90/ Die Grünen	stern.de	0.005	0.003	1.689	0.091
2: B90/ Die Grünen	Tagesschau.de	-0.003	0.004	-0.805	0.421
2: B90/ Die Grünen	DIE WELT	-0.004	0.003	-1.160	0.246
2: B90/ Die Grünen	ZEIT ONLINE	0.004	0.004	1.035	0.301
4: Great Coalition debates	(Intercept)	0.064	0.005	13.210	0.000
4: Great Coalition debates	FOCUS ONLINE	-0.010	0.006	-1.698	0.089
4: Great Coalition debates	SPIEGEL ONLINE	0.003	0.006	0.487	0.626
4: Great Coalition debates	stern.de	-0.032	0.006	-5.472	0.000
4: Great Coalition debates	Tagesschau.de	-0.005	0.006	-0.841	0.401
4: Great Coalition debates	DIE WELT	-0.012	0.006	-2.183	0.029
4: Great Coalition debates	ZEIT ONLINE	0.002	0.006	0.400	0.689
10: M.Schulz, vs. A.Merkel	(Intercept)	0.009	0.002	4.131	0.000
10: M.Schulz, vs. A.Merkel	FOCUS ONLINE	0.001	0.003	0.192	0.848
10: M.Schulz, vs. A.Merkel	SPIEGEL ONLINE	0.002	0.003	0.565	0.572
10: M.Schulz, vs. A.Merkel	stern.de	0.007	0.003	2.860	0.004
10: M.Schulz, vs. A.Merkel	Tagesschau.de	0.003	0.003	0.991	0.322
10: M.Schulz, vs. A.Merkel	DIE WELT	-0.003	0.003	-1.117	0.264
10: M.Schulz, vs. A.Merkel	ZEIT ONLINE	0.012	0.003	3.798	0.000
13: A.Merkel, election campaign	(Intercept)	0.024	0.003	9.704	0.000
13: A.Merkel, election campaign	FOCUS ONLINE	0.002	0.003	0.550	0.582
13: A.Merkel, election campaign	SPIEGEL ONLINE	0.003	0.003	0.992	0.321
13: A.Merkel, election campaign	stern.de	0.009	0.003	2.709	0.007
13: A.Merkel, election campaign	Tagesschau.de	-0.006	0.003	-1.824	0.068
13: A.Merkel, election campaign	DIE WELT	0.001	0.003	0.297	0.767
13: A.Merkel, election campaign	ZEIT ONLINE	0.004	0.004	1.137	0.256
17: Debates within SPD	(Intercept)	0.035	0.003	10.632	0.000
17: Debates within SPD	FOCUS ONLINE	-0.005	0.004	-1.315	0.189
17: Debates within SPD	SPIEGEL ONLINE	-0.009	0.004	-2.186	0.029
17: Debates within SPD	stern.de	-0.001	0.004	-0.361	0.718
17: Debates within SPD	Tagesschau.de	-0.013	0.005	-2.809	0.005
17: Debates within SPD	DIE WELT	-0.010	0.004	-2.612	0.009
17: Debates within SPD	ZEIT ONLINE	-0.007	0.005	-1.579	0.114
20: AfD, right-wing radicalism	(Intercept)	0.017	0.003	5.704	0.000
20: AfD, right-wing radicalism	FOCUS ONLINE	-0.002	0.004	-0.607	0.544
20: AfD, right-wing radicalism	SPIEGEL ONLINE	-0.003	0.004	-0.724	0.469
20: AfD, right-wing radicalism	stern.de	-0.003	0.004	-0.784	0.433
20: AfD, right-wing radicalism	Tagesschau.de	-0.000	0.004	-0.033	0.973
20: AfD, right-wing radicalism	DIE WELT	0.002	0.004	0.512	0.609
20: AfD, right-wing radicalism	ZEIT ONLINE	-0.002	0.004	-0.538	0.590
22: SPD, stuffing debates	(Intercept)	0.019	0.003	7.408	0.000
22: SPD, stuffing debates	FOCUS ONLINE	-0.004	0.003	-1.170	0.242
22: SPD, stuffing debates	SPIEGEL ONLINE	0.010	0.003	2.960	0.003
22: SPD, stuffing debates	stern.de	-0.006	0.003	-1.943	0.052
22: SPD, stuffing debates	Tagesschau.de	-0.003	0.003	-0.903	0.367
22: SPD, stuffing debates	DIE WELT	-0.004	0.003	-1.308	0.191
22: SPD, stuffing debates	ZEIT ONLINE	0.005	0.003	1.449	0.147
23: CSU, Söder & Seehover	(Intercept)	0.035	0.004	9.191	0.000
23: CSU, Söder & Seehover	FOCUS ONLINE	-0.004	0.005	-0.887	0.375
23: CSU, Söder & Seehover	SPIEGEL ONLINE	0.006	0.005	1.094	0.274
23: CSU, Söder & Seehover	stern.de	-0.002	0.005	-0.365	0.715
23: CSU, Söder & Seehover	Tagesschau.de	-0.006	0.005	-1.214	0.225
23: CSU, Söder & Seehover	DIE WELT	-0.006	0.004	-1.238	0.216
23: CSU, Söder & Seehover	ZEIT ONLINE	0.002	0.005	0.357	0.721
26: Jamaica fail, Reelections or GroKo?	(Intercept)	0.035	0.003	11.775	0.000
26: Jamaica fail, Reelections or GroKo?	FOCUS ONLINE	-0.004	0.004	-1.137	0.256
26: Jamaica fail, Reelections or GroKo?	SPIEGEL ONLINE	-0.004	0.004	-1.076	0.282
26: Jamaica fail, Reelections or GroKo?	stern.de	-0.012	0.004	-3.463	0.001
26: Jamaica fail, Reelections or GroKo?	Tagesschau.de	-0.010	0.004	-2.584	0.010
26: Jamaica fail, Reelections or GroKo?	DIE WELT	-0.012	0.004	-3.333	0.001
26: Jamaica fail, Reelections or GroKo?	ZEIT ONLINE	-0.005	0.004	-1.356	0.175
27: Jamaica Coalition debates	(Intercept)	0.066	0.005	13.865	0.000
27: Jamaica Coalition debates	FOCUS ONLINE	-0.029	0.006	-5.152	0.000
27: Jamaica Coalition debates	SPIEGEL ONLINE	-0.009	0.006	-1.438	0.150
27: Jamaica Coalition debates	stern.de	-0.028	0.006	-5.088	0.000
27: Jamaica Coalition debates	Tagesschau.de	-0.018	0.006	-2.939	0.003
27: Jamaica Coalition debates	DIE WELT	-0.008	0.005	-1.416	0.157
27: Jamaica Coalition debates	ZEIT ONLINE	-0.003	0.007	-0.460	0.645
30: AfD, F.Petry & Meuthen	(Intercept)	0.026	0.003	7.579	0.000
30: AfD, F.Petry & Meuthen	FOCUS ONLINE	-0.005	0.004	-1.168	0.243
30: AfD, F.Petry & Meuthen	SPIEGEL ONLINE	0.002	0.004	0.430	0.667
30: AfD, F.Petry & Meuthen	stern.de	-0.004	0.004	-0.896	0.370
30: AfD, F.Petry & Meuthen	Tagesschau.de	-0.014	0.004	-3.035	0.002
30: AfD, F.Petry & Meuthen	DIE WELT	-0.011	0.004	-2.812	0.005
30: AfD, F.Petry & Meuthen	ZEIT ONLINE	0.004	0.005	0.914	0.361
32: AfD, Gauland & Weidel	(Intercept)	0.023	0.004	6.308	0.000
32: AfD, Gauland & Weidel	FOCUS ONLINE	0.001	0.004	0.191	0.848
32: AfD, Gauland & Weidel	SPIEGEL ONLINE	-0.001	0.005	-0.123	0.902
32: AfD, Gauland & Weidel	stern.de	0.007	0.004	1.593	0.111
32: AfD, Gauland & Weidel	Tagesschau.de	-0.006	0.005	-1.221	0.222
32: AfD, Gauland & Weidel	DIE WELT	0.006	0.004	1.378	0.168
32: AfD, Gauland & Weidel	ZEIT ONLINE	0.006	0.005	1.198	0.231
37: AfD & DIE LINKE in parliament	(Intercept)	0.024	0.004	6.652	0.000
37: AfD & DIE LINKE in parliament	FOCUS ONLINE	0.005	0.004	1.221	0.222
37: AfD & DIE LINKE in parliament	SPIEGEL ONLINE	0.013	0.005	2.984	0.003
37: AfD & DIE LINKE in parliament	stern.de	0.001	0.004	0.252	0.801
37: AfD & DIE LINKE in parliament	Tagesschau.de	0.005	0.005	1.130	0.258
37: AfD & DIE LINKE in parliament	DIE WELT	0.002	0.004	0.483	0.629
37: AfD & DIE LINKE in parliament	ZEIT ONLINE	0.011	0.005	2.143	0.032
46: CDU	(Intercept)	0.018	0.002	7.336	0.000
46: CDU	FOCUS ONLINE	-0.001	0.003	-0.245	0.806
46: CDU	SPIEGEL ONLINE	0.002	0.003	0.753	0.451
46: CDU	stern.de	-0.006	0.003	-1.942	0.052
46: CDU	Tagesschau.de	-0.011	0.003	-3.364	0.001
46: CDU	DIE WELT	-0.001	0.003	-0.403	0.687
46: CDU	ZEIT ONLINE	-0.000	0.003	-0.023	0.982

A.4 Sentiment Values (monthly aggregated)

date	topic	Number of Obs.	sentiment value * 1000
2017-06-01	1: SPD, M.Schulz	51	-0.04
2017-07-01	1: SPD, M.Schulz	20	-0.01
2017-08-01	1: SPD, M.Schulz	49	-0.02
2017-09-01	1: SPD, M.Schulz	103	-0.05
2017-10-01	1: SPD, M.Schulz	42	-0.01
2017-11-01	1: SPD, M.Schulz	34	-0.04
2017-12-01	1: SPD, M.Schulz	24	-0.04
2018-01-01	1: SPD, M.Schulz	29	-0.02
2018-02-01	1: SPD, M.Schulz	47	-0.18
2017-06-01	2: B90/ Die Grünen	50	-0.08
2017-07-01	2: B90/ Die Grünen	8	-0.00
2017-08-01	2: B90/ Die Grünen	8	-0.01
2017-09-01	2: B90/ Die Grünen	51	-0.01
2017-10-01	2: B90/ Die Grünen	12	-0.02
2017-11-01	2: B90/ Die Grünen	22	-0.02
2017-12-01	2: B90/ Die Grünen	31	-0.03
2018-01-01	2: B90/ Die Grünen	59	-0.06
2018-02-01	2: B90/ Die Grünen	1	-0.00
2017-06-01	4: Great Coalition debates	1	-0.00
2017-09-01	4: Great Coalition debates	2	-0.00
2017-10-01	4: Great Coalition debates	1	-0.00
2017-11-01	4: Great Coalition debates	84	-0.07
2017-12-01	4: Great Coalition debates	219	-0.15
2018-01-01	4: Great Coalition debates	382	-0.29
2018-02-01	4: Great Coalition debates	119	-0.03
2017-06-01	10: M.Schulz, vs. A.Merkel	11	-0.02
2017-07-01	10: M.Schulz, vs. A.Merkel	50	-0.06
2017-08-01	10: M.Schulz, vs. A.Merkel	19	-0.01
2017-09-01	10: M.Schulz, vs. A.Merkel	56	-0.02
2017-10-01	10: M.Schulz, vs. A.Merkel	1	-0.00
2017-11-01	10: M.Schulz, vs. A.Merkel	4	-0.00
2017-12-01	10: M.Schulz, vs. A.Merkel	7	-0.00
2018-01-01	10: M.Schulz, vs. A.Merkel	5	-0.01
2018-02-01	10: M.Schulz, vs. A.Merkel	5	-0.03
2017-06-01	13: A.Merkel, election campaign	56	-0.04
2017-07-01	13: A.Merkel, election campaign	13	-0.02
2017-08-01	13: A.Merkel, election campaign	40	-0.04
2017-09-01	13: A.Merkel, election campaign	98	-0.05
2017-10-01	13: A.Merkel, election campaign	6	-0.01
2017-11-01	13: A.Merkel, election campaign	18	-0.01
2017-12-01	13: A.Merkel, election campaign	17	-0.01
2018-01-01	13: A.Merkel, election campaign	7	-0.01
2018-02-01	13: A.Merkel, election campaign	17	-0.05
2017-06-01	17: Debates within SPD	14	-0.00
2017-07-01	17: Debates within SPD	1	-0.00
2017-08-01	17: Debates within SPD	9	-0.02
2017-09-01	17: Debates within SPD	13	-0.02
2017-10-01	17: Debates within SPD	13	-0.01
2017-11-01	17: Debates within SPD	20	-0.04
2017-12-01	17: Debates within SPD	70	-0.07
2018-01-01	17: Debates within SPD	122	-0.16
2018-02-01	17: Debates within SPD	161	-0.30
2017-06-01	20: AfD, right-wing radicalism	19	-0.05
2017-07-01	20: AfD, right-wing radicalism	19	-0.04
2017-08-01	20: AfD, right-wing radicalism	58	-0.19
2017-09-01	20: AfD, right-wing radicalism	32	-0.03
2017-10-01	20: AfD, right-wing radicalism	31	-0.06
2017-11-01	20: AfD, right-wing radicalism	15	-0.02
2017-12-01	20: AfD, right-wing radicalism	21	-0.02
2018-01-01	20: AfD, right-wing radicalism	30	-0.05
2018-02-01	20: AfD, right-wing radicalism	15	-0.08
2017-06-01	22: SPD, stuffing debates	4	-0.00
2017-07-01	22: SPD, stuffing debates	11	0.01
2017-08-01	22: SPD, stuffing debates	4	-0.00
2017-09-01	22: SPD, stuffing debates	43	-0.04
2017-10-01	22: SPD, stuffing debates	34	-0.03
2017-11-01	22: SPD, stuffing debates	19	-0.01
2017-12-01	22: SPD, stuffing debates	19	-0.01
2018-01-01	22: SPD, stuffing debates	22	-0.02
2018-02-01	22: SPD, stuffing debates	48	-0.09
2017-06-01	23: CSU, Söder & Seehover	1	-0.00
2017-07-01	23: CSU, Söder & Seehover	25	-0.00
2017-08-01	23: CSU, Söder & Seehover	13	-0.02
2017-09-01	23: CSU, Söder & Seehover	70	-0.06
2017-10-01	23: CSU, Söder & Seehover	125	-0.15
2017-11-01	23: CSU, Söder & Seehover	105	-0.12
2017-12-01	23: CSU, Söder & Seehover	83	-0.00
2018-01-01	23: CSU, Söder & Seehover	16	-0.02
2018-02-01	23: CSU, Söder & Seehover	23	-0.01
2017-06-01	26: Jamaica fail, Reelections or GroKo?	3	-0.00
2017-07-01	26: Jamaica fail, Reelections or GroKo?	3	-0.00
2017-08-01	26: Jamaica fail, Reelections or GroKo?	5	-0.01
2017-09-01	26: Jamaica fail, Reelections or GroKo?	11	-0.01
2017-10-01	26: Jamaica fail, Reelections or GroKo?	7	-0.01
2017-11-01	26: Jamaica fail, Reelections or GroKo?	230	-0.28
2017-12-01	26: Jamaica fail, Reelections or GroKo?	29	-0.04
2018-01-01	26: Jamaica fail, Reelections or GroKo?	17	-0.03
2018-02-01	26: Jamaica fail, Reelections or GroKo?	10	-0.02
2017-06-01	27: Jamaica Coalition debates	7	-0.00
2017-07-01	27: Jamaica Coalition debates	8	-0.00
2017-08-01	27: Jamaica Coalition debates	8	-0.02
2017-09-01	27: Jamaica Coalition debates	69	-0.06
2017-10-01	27: Jamaica Coalition debates	233	0.01
2017-11-01	27: Jamaica Coalition debates	418	-0.36
2017-12-01	27: Jamaica Coalition debates	46	-0.06
2018-01-01	27: Jamaica Coalition debates	7	-0.01
2018-02-01	27: Jamaica Coalition debates	2	-0.02
2017-06-01	30: AfD, F.Petry & Meuthen	16	-0.02
2017-07-01	30: AfD, F.Petry & Meuthen	27	-0.07
2017-08-01	30: AfD, F.Petry & Meuthen	27	-0.07
2017-09-01	30: AfD, F.Petry & Meuthen	88	-0.05
2017-10-01	30: AfD, F.Petry & Meuthen	55	-0.10
2017-11-01	30: AfD, F.Petry & Meuthen	31	-0.01
2017-12-01	30: AfD, F.Petry & Meuthen	27	-0.05
2018-01-01	30: AfD, F.Petry & Meuthen	6	-0.01
2018-02-01	30: AfD, F.Petry & Meuthen	5	-0.01
2017-06-01	32: AfD, Gauland & Weidel	20	-0.04
2017-07-01	32: AfD, Gauland & Weidel	17	-0.03
2017-08-01	32: AfD, Gauland & Weidel	34	-0.08
2017-09-01	32: AfD, Gauland & Weidel	167	-0.14
2017-10-01	32: AfD, Gauland & Weidel	24	-0.02
2017-11-01	32: AfD, Gauland & Weidel	24	-0.03
2017-12-01	32: AfD, Gauland & Weidel	71	-0.04
2018-01-01	32: AfD, Gauland & Weidel	29	-0.06
2018-02-01	32: AfD, Gauland & Weidel	29	-0.09
2017-06-01	37: AfD & DIE LINKE in parliament	10	-0.02
2017-08-01	37: AfD & DIE LINKE in parliament	4	-0.00
2017-09-01	37: AfD & DIE LINKE in parliament	65	-0.03
2017-10-01	37: AfD & DIE LINKE in parliament	138	-0.15
2017-11-01	37: AfD & DIE LINKE in parliament	34	-0.03
2017-12-01	37: AfD & DIE LINKE in parliament	37	-0.06
2018-01-01	37: AfD & DIE LINKE in parliament	95	-0.15
2018-02-01	37: AfD & DIE LINKE in parliament	16	-0.04
2017-06-01	46: CDU	13	-0.01
2017-07-01	46: CDU	16	-0.03
2017-08-01	46: CDU	31	-0.05
2017-09-01	46: CDU	17	-0.02
2017-10-01	46: CDU	39	-0.07
2017-11-01	46: CDU	18	-0.01
2017-12-01	46: CDU	20	-0.02
2018-01-01	46: CDU	11	-0.01
2018-02-01	46: CDU	30	-0.06

A.5 Sentiment Values (aggregated by news website)

News website	topic	Number of Obs.	sentiment value * 1000
Bild.de	1: SPD, M.Schulz	44	-0.08
Bild.de	10: M.Schulz, vs. A.Merkel	10	-0.01
Bild.de	13: A.Merkel, election campaign	18	-0.01
Bild.de	17: Debates within SPD	46	-0.06
Bild.de	2: B90/ Die Grünen	21	-0.00
Bild.de	20: AfD, right-wing radicalism	22	-0.06
Bild.de	22: SPD, stuffing debates	19	-0.02
Bild.de	23: CSU, Söder & Seehover	38	-0.04
Bild.de	26: Jamaica fail, Reelections or GroKo?	43	-0.09
Bild.de	27: Jamaica Coalition debates	96	-0.11
Bild.de	30: AfD, F.Petry & Meuthen	30	-0.04
Bild.de	32: AfD, Gauland & Weidel	28	-0.04
Bild.de	37: AfD & DIE LINKE in parliament	30	-0.05
Bild.de	4: Great Coalition debates	83	-0.08
Bild.de	46: CDU	17	-0.03
DIE WELT	1: SPD, M.Schulz	71	-0.02
DIE WELT	10: M.Schulz, vs. A.Merkel	19	-0.02
DIE WELT	13: A.Merkel, election campaign	50	-0.02
DIE WELT	17: Debates within SPD	70	-0.05
DIE WELT	2: B90/ Die Grünen	34	-0.03
DIE WELT	20: AfD, right-wing radicalism	62	-0.07
DIE WELT	22: SPD, stuffing debates	34	-0.01
DIE WELT	23: CSU, Söder & Seehover	78	-0.04
DIE WELT	26: Jamaica fail, Reelections or GroKo?	54	-0.04
DIE WELT	27: Jamaica Coalition debates	188	-0.06
DIE WELT	30: AfD, F.Petry & Meuthen	40	-0.03
DIE WELT	32: AfD, Gauland & Weidel	108	-0.07
DIE WELT	37: AfD & DIE LINKE in parliament	75	-0.05
DIE WELT	4: Great Coalition debates	166	-0.07
DIE WELT	46: CDU	49	-0.04
FOCUS ONLINE	1: SPD, M.Schulz	84	-0.06
FOCUS ONLINE	10: M.Schulz, vs. A.Merkel	23	-0.03
FOCUS ONLINE	13: A.Merkel, election campaign	50	-0.02
FOCUS ONLINE	17: Debates within SPD	78	-0.08
FOCUS ONLINE	2: B90/ Die Grünen	33	-0.01
FOCUS ONLINE	20: AfD, right-wing radicalism	43	-0.05
FOCUS ONLINE	22: SPD, stuffing debates	32	-0.02
FOCUS ONLINE	23: CSU, Söder & Seehover	74	-0.05
FOCUS ONLINE	26: Jamaica fail, Reelections or GroKo?	56	-0.06
FOCUS ONLINE	27: Jamaica Coalition debates	103	-0.09
FOCUS ONLINE	30: AfD, F.Petry & Meuthen	48	-0.02
FOCUS ONLINE	32: AfD, Gauland & Weidel	68	-0.07
FOCUS ONLINE	37: AfD & DIE LINKE in parliament	73	-0.06
FOCUS ONLINE	4: Great Coalition debates	144	-0.06
FOCUS ONLINE	46: CDU	47	-0.03
SPIEGEL ONLINE	1: SPD, M.Schulz	46	-0.05
SPIEGEL ONLINE	10: M.Schulz, vs. A.Merkel	18	-0.02
SPIEGEL ONLINE	13: A.Merkel, election campaign	30	-0.02
SPIEGEL ONLINE	17: Debates within SPD	44	-0.05
SPIEGEL ONLINE	2: B90/ Die Grünen	34	-0.04
SPIEGEL ONLINE	20: AfD, right-wing radicalism	25	-0.06
SPIEGEL ONLINE	22: SPD, stuffing debates	46	-0.04
SPIEGEL ONLINE	23: CSU, Söder & Seehover	78	-0.07
SPIEGEL ONLINE	26: Jamaica fail, Reelections or GroKo?	44	-0.06
SPIEGEL ONLINE	27: Jamaica Coalition debates	117	-0.07
SPIEGEL ONLINE	30: AfD, F.Petry & Meuthen	48	-0.07
SPIEGEL ONLINE	32: AfD, Gauland & Weidel	48	-0.05
SPIEGEL ONLINE	37: AfD & DIE LINKE in parliament	64	-0.08
SPIEGEL ONLINE	4: Great Coalition debates	135	-0.06
SPIEGEL ONLINE	46: CDU	28	-0.05
stern.de	1: SPD, M.Schulz	85	-0.02
stern.de	10: M.Schulz, vs. A.Merkel	38	-0.01
stern.de	13: A.Merkel, election campaign	71	-0.04
stern.de	17: Debates within SPD	105	-0.06
stern.de	2: B90/ Die Grünen	65	-0.03
stern.de	20: AfD, right-wing radicalism	41	-0.04
stern.de	22: SPD, stuffing debates	28	-0.02
stern.de	23: CSU, Söder & Seehover	94	-0.04
stern.de	26: Jamaica fail, Reelections or GroKo?	53	-0.04
stern.de	27: Jamaica Coalition debates	115	-0.05
stern.de	30: AfD, F.Petry & Meuthen	57	-0.05
stern.de	32: AfD, Gauland & Weidel	86	-0.06
stern.de	37: AfD & DIE LINKE in parliament	60	-0.05
stern.de	4: Great Coalition debates	87	-0.04
stern.de	46: CDU	21	-0.00
Tagesschau.de	1: SPD, M.Schulz	36	-0.04
Tagesschau.de	10: M.Schulz, vs. A.Merkel	20	-0.01
Tagesschau.de	13: A.Merkel, election campaign	21	-0.02
Tagesschau.de	17: Debates within SPD	38	-0.03
Tagesschau.de	2: B90/ Die Grünen	24	-0.02
Tagesschau.de	20: AfD, right-wing radicalism	24	-0.05
Tagesschau.de	22: SPD, stuffing debates	18	0.01
Tagesschau.de	23: CSU, Söder & Seehover	50	-0.06
Tagesschau.de	26: Jamaica fail, Reelections or GroKo?	35	-0.04
Tagesschau.de	27: Jamaica Coalition debates	77	-0.03
Tagesschau.de	30: AfD, F.Petry & Meuthen	19	-0.03
Tagesschau.de	32: AfD, Gauland & Weidel	28	-0.04
Tagesschau.de	37: AfD & DIE LINKE in parliament	50	-0.04
Tagesschau.de	4: Great Coalition debates	95	-0.03
Tagesschau.de	46: CDU	9	-0.02
ZEIT ONLINE	1: SPD, M.Schulz	33	-0.03
ZEIT ONLINE	10: M.Schulz, vs. A.Merkel	30	-0.03
ZEIT ONLINE	13: A.Merkel, election campaign	32	-0.04
ZEIT ONLINE	17: Debates within SPD	42	-0.04
ZEIT ONLINE	2: B90/ Die Grünen	31	-0.04
ZEIT ONLINE	20: AfD, right-wing radicalism	23	-0.06
ZEIT ONLINE	22: SPD, stuffing debates	27	-0.03
ZEIT ONLINE	23: CSU, Söder & Seehover	49	-0.03
ZEIT ONLINE	26: Jamaica fail, Reelections or GroKo?	30	-0.05
ZEIT ONLINE	27: Jamaica Coalition debates	102	-0.09
ZEIT ONLINE	30: AfD, F.Petry & Meuthen	40	-0.08
ZEIT ONLINE	32: AfD, Gauland & Weidel	49	-0.07
ZEIT ONLINE	37: AfD & DIE LINKE in parliament	47	-0.05
ZEIT ONLINE	4: Great Coalition debates	98	-0.12

A.6 Cross Correlation Coefficient (lag 0)

	Var1	AfD	FDP	Grüne	Linke	SPD	Union
1	1: SPD, M.Schulz	-0.636	0.072	-0.438	-0.693	0.752	0.199
2	10: M.Schulz, vs. A.Merkel	0.438	0.566	0.505	0.341	-0.229	-0.758
3	13: A.Merkel, election campaign	0.098	0.350	0.440	-0.060	0.076	-0.507
4	17: Debates within SPD	-0.770	0.075	-0.676	-0.754	0.841	0.382
5	2: B90/ Die Grünen	0.253	-0.092	0.185	0.480	-0.329	-0.048
6	20: AfD, right-wing radicalism	0.225	0.369	0.224	0.037	-0.157	-0.319
7	22: SPD, stuffing debates	-0.710	-0.112	-0.465	-0.797	0.877	0.302
8	23: CSU, Söder & Seehover	-0.169	-0.897	-0.249	-0.283	0.145	0.565
9	26: Jamaica fail, Reelections or GroKo?	-0.251	-0.501	-0.388	-0.258	0.047	0.537
10	27: Jamaica Coalition debates	-0.197	-0.439	-0.266	-0.222	0.000	0.436
11	30: AfD, F.Petry & Meuthen	0.410	-0.032	0.351	0.296	-0.348	-0.224
12	32: AfD, Gauland & Weidel	-0.220	0.430	0.221	-0.315	0.336	-0.296
13	37: AfD & DIE LINKE in parliament	-0.217	-0.521	-0.418	-0.003	0.238	0.552
14	4: Great Coalition debates	-0.165	0.336	-0.361	0.292	-0.126	0.228
15	46: CDU	-0.083	-0.066	-0.108	-0.286	0.285	-0.007