# 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 \citep{vuma\_arbeitsgemeinschaft\_verbrauchs-\_und\_medienanalyse\_verbrauchs-\_2017}.

The pluralism of not only online media, but (of) 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 01.06.2017 to 01.03.2018 and thus inform their readers ~~both~~ about both the election promises of the parties (before the election) and (about) 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 \citep{hansen\_shocking\_2016}. This means that the topics discussed in the articles are identified first (topic), followed by an analysis of how they are discussed ~~with~~ by the various news websites (tone). The final step is to check whether the tonality of reporting is reflected ~~in~~ 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 corpus, the structural topic modeling (STM) developed by \citet{roberts\_model\_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 (to incorporate)/the incorporation of external variables that affect both topical content and topical prevalence. I estimate a model (where)/in which the news website is included as a control for both the topical content and the topical prevalence. The result of the generative process of STM are two posterior distributions: One for the topic prevalence in an article and one for the content of a topic. The latter is used to label the topics according to an event or issue discussed in the media. The topic prevalence of an article (or the posterior distribution) 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. 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 list 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.
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 value of individual topics from \ref{item\_2} and the survey value of a specific party is estimated using the cross correlation function (CCF).

Approach 1 has been used in \citet{roberts\_model\_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). \citet{hansen\_shocking\_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 ~~about~~ of political trends in the past six month (June 2017 to March 2018). The data used to conduct the model is described in Section \ref{ch\_data}. Section \ref{ch\_model} 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 \ref{ch\_empirical}.

# 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 the AfD a political upswing by taking up the dissatisfaction of parts of the population and using it to raise its own profile. Leading party members of the AfD as well as party supporters repeatedly accused the mass media in the course of the reporting on the federal elections to report unilaterally and to present the AfD intentionally 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 19 November 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 (of the Liberals). 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 \ref{fig\_polls} 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. However, the polling 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 \ref{ch\_correlation} examines whether there is a correlation between the survey results and the way the parties are reported about in the media.

# 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\footnote{Bild.de, DIE WELT, FOCUS ONLINE, SPIEGEL ONLINE, stern.de, ZEIT ONLINE, Tagesschau.de}. The articles are dated from 01.06.2017 to 01.03.2018. I first extract all online articles using the Webhose.io API.\footnote{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.} 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\footnote{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.} - 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 offers video content and the DLF (Deutschlandfunk) website mainly offers audio content in the form of interviews, which makes it hard to include it in the model.

Figure \ref{fig\_distr1} 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 failure of the Jamaica coalition talks on November, 19th (indicated by the red dotted lines). Figure \ref{fig\_distr2} shows~~,~~ that DIE WELT published the most ~~the~~ articles on domestic policy, followed by stern.de and FOCUS ONLINE.

Looking at the histograms of the word counts (Figure \ref{fig\_wordcount}), 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 are 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.

The longest article at Tagesschau.de contains 2006 words, nevertheless the median value is comparatively large (see Table \label{t\_wordcount}). 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 the frequency of words are represented by their size. Intuitively the term frequency (tf) of a word is a measure of how important that word may be. The word cloud in Figure \ref{fig\_wordcloud1} is derived from all articles within the dataset. As can be seen, problems arise with words that are highly frequent. For example "die" (eng. "the"), "und" (eng. "and"), and "in" (eng. "in") are extremely common but unrelated to the quantity of interest. These terms, often called stop words \citep{gentzkow\_text\_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 (stop-word removal and stemming) based on the nature of the data (twitter text, newspaper articles, speeches, etc.) \citep{gentzkow\_text\_2017}. 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 \citep{bholat\_text\_2015}.

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.\footnote{https://tartarus.org/martin/PorterStemmer/} To remove distorting words, the pre-defined stop word list from the Snowball project\footnote{http://snowball.tartarus.org/algorithms/german/stop.txt} is used together with a customized list of stop-words. Additionally punctuation character (e.g. ., ,, !, ?, etc.) and all numbers are removed from our corpus. After completing these steps we were left with 68.576 unique terms in our vocabulary. The following wordclouds are derived from the corpus for each news provider. 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 corpuses of the different news providers.

To use the data for statistical analysis, the next step is to divide the whole corpus 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. Next, for each document $d \in \lbrace 1,...,D \rbrace$ 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 $v \in \lbrace 1,...,V \rbrace$ 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. This representation is often referred to as the bag of words model \citep{gentzkow\_text\_2017}, since the order in which words are used within a document is disregarded. The sum of all documents forms what is called the corpus.

# The structural topic model

# 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 $\theta\_{dk}$ is used ~~in order~~ to estimate the conditional expectation of topic prevalence for given document characteristics (See section \ref{subsection\_topic}). 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 analysis (see section \ref{subsection\_tone}). 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 \ref{ch\_correlation}.

## Topic

In order to give an initial overview of the results, Figure \ref{fig\_topic\_proportion} 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 \citep{roberts\_model\_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.

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 \ref{apx\_tf}:

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/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 applied to each topic $k$, where the documents are observations, the dependent variable is the posterior probability of the respective topic ($\theta\_{d}$) and the covariates are dummy variables that are 1 if the document was published by the respective website and 0 otherwise (see equation \ref{eq\_1}). As the dependent variable is a vector containing proportions that sum up to 1, the QR decomposition of the model is computed prior to the estimation of the coefficients. 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 \citep{roberts\_model\_2016}.

Figure \ref{fig\_estimateEffects} shows the regression results for the ~~above selected~~ topics selected above (See Appendix \ref{apx\_coeff} 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. 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 grand coalition. 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.

## Tone

The sentiment analysis is performed with the documents 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 ~~on~~ 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 (\citet{nyman\_news\_2018} \citep{tetlock\_giving\_2007}, \citep{tetlock\_more\_2008}). \citet{hansen\_shocking\_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 multi-dimensional information a statement is transmitting, they apply LDA on a corpus of 142 FOMC decision statements split into sentences (topic). They then measure how the central bank is talking about that topic, using a dictionary approach (tone). 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 \citet{nyman\_news\_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\footnote{SentiWS for short. available here: http://wortschatz.uni-leipzig.de/de/download}, 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 word forms including their inflections, respectively. 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:

Figure \ref{fig\_sentscore\_monthly} shows the results of the analysis for each topic on a monthly basis, 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 illustration. First of all, it can be seen that, on 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). In the following month (November 2017), after it became clear that there would be no coalition between the CDU/CSU, FDP and Die Grünen, the value of this topic as well as that of topic 26 drops rapidly, but then rises again in February. Concerning the issues that discuss the great coalition between CDU/CSU and SPD, 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.

In order to analyze the differences between the news websites, two different figures are considered: The bar plot is used to examine the polarity tendencies of the individual topics for a the respective website (Figure \ref{fig\_sentscore\_site}) and the radar plot is considered to observe the differences between the websites (Figure \ref{fig\_sentscore\_radar}).

Starting with the bar plot it becomes apparent that all topics are discussed negatively, except topic 23 at Tagesschau.de. At Bild.de, the topics that include the coalition negotiations (26, 27, 4) and the SPD (1, 17) are the most negative. 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.

A good overview of how differently the topics are discussed by the providers is shown in Figure \ref{fig\_sentscore\_radar}. 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 negotiations 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.

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

* The sentiment value of the SPD is decreasing over time, especially regarding debates within the party (topic 17).
* 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.
* In contrast, the tonality of the topics in relation to the AfD shows rather small differences.
* 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.

## News sentiment and poll data

This section seeks to examine the association between sentiment reflected in online news content and phone survey 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.\footnote{https://www.infratest-dimap.de/umfragen-analysen/bundesweit/sonntagsfrage/} 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. \citet{tumasjan\_predicting\_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.

citet{fu\_analyzing\_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 \citep{box\_time\_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, \citet{padmaja\_evaluating\_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.

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 the cross correlation estimation shown in Figure \ref{fig\_ccf}, the significant correlations between topic sentiment and survey value are evaluated for each party.\footnote{The value of the cross correlation coefficients for lag 0 can be found in the Appendix (Table \ref{apx\_corr})} It is important to note that no causal relationships are described below, but that only the correlation between the two time series is described.

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 ~~have gone~~ 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 ($x\_{t+1}$).

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

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

# Conclusion

The purpose of this paper was to examine (1) whether the political reporting of different media differs in terms of topic frequency and topic tonality and (2) whether this reporting correlates with the opinion-forming process of the voters. 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 overall all topics are discussed negatively, there are still differences, especially regarding the coalition negotiations. The smallest differences can be found for topic concerning the AfD. 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. Further research should focus on the exact causal relationships between these two concepts.