

Political news coverage of online news

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Introduction

In democracies, the media fulfill fundamental functions: They should inform the people, contribute to the formation of opinion through criticism and discussion and thus enable participation. In recent decades, however, concern has grown about the role of the media in politics in general and in election campaigns in particular. They are criticized for influencing election results through their reporting and for helping populist parties in particular to flourish. After the 2017 federal elections in Germany, for example, the media were accused of contributing to the success of the right-wing populist AfD by increasingly including the party's content and using the same language in their articles as the AfD. Representatives of these media houses strongly opposed this accusation. The purpose of this study is to examine whether there is evidence that support the accusation of biased media reporting, especially during election campaigns.

For advertising-financed media the battle for the attention of the recipients is at the center of economic decisions. Online media in particular, which offer their content to a large extent free of charge and generate their revenue through advertising space, compete for the scarce resource of attention. Consumers pay a non-monetary price providing their attention, which the media platform bundles and sells on to advertising customers. This business model corresponds to that of a platform market, in which media companies act as platforms that connect the market of advertising with the reader market to exploit the indirect network effects between them (Dewenter and Rösch 2014). A profit-maximizing publisher therefore directs its economic decisions according to what will attract the most attention.

This conclusion, derived from the economic theory of platform markets, corresponds to the notion of media logic, a central concept in the field of media and communication studies (Takens et al. 2013). The debate about media logic is embedded in the broader discussion about the interaction between the press, politics and the public. The underlying thesis is that the content of political news is the product of news values and narrative techniques that media use to attract audiences (Strömbäck 2008). According to Takens et al. (2013), three content attributes highly correspond with news values and influence how journalists interpret political events: 1) personalized content, i.e., the focus on individual politicians; 2) the framing of politics as a contest and 3) negative coverage. Similarly Blassnig et al. (2019) states that media primarily focus on news factors, i.e. the factors that turn an event into news worth reporting like conflict, drama, negativity, surprise or proximity. Likewise populist messages often co-occur with negative, emotionalized, or dramatized communication style, thus utilizing similar mechanisms as the media logic, respectively the attention economy. In fact, Blassnig et al. (2019) shows that populist key messages by political and media actors in news articles provoke more reader comments under these articles. Media competing for the attention of readers therefore have an incentive to pick up on the key messages of these parties.

But does increased reporting also lead to rising survey results? Especially if this reporting is largely negative, which is the case for reporting on AfD during electing campaign phase . In political science, several studies have examined at least the first aspect of this question (see for example Druckman and Parkin (2005), Eberl (2018)). In general, it is assumed that smaller, non-established parties in particular benefit from placing

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their topics in the media in order to get them into the voters' heads. Here, the tendency of the reporting is irrelevant but rather the quantity is decisive.

However, the causal relationship between reporting and voter preferences is not the subject of this study. Rather, it is intended to investigate how the reporting of online news is similar to the messaging of different political parties. Especially during election campaigns political parties want the media agenda to be congruent with their own agenda to define the issue-based criteria on which they will be evaluated by voters (Eberl, Boomgaarden, and Wagner 2017). Parties instrumentalize their public relations in order to highlight issues that they are perceived to be competent on, that they “own” and that are important to their voters (Kepplinger and Maurer 2004). This paper therefore analyzes the period before and after the 2017 federal elections in Germany to answer the question whether political news report about similar topics and if this similarity changes after the election campaign is over.

In order to answer these and other media-related questions in the political context, quantifying the content of media is a prerequisite. One of the key challenges is to determine the features that are used to describe media content (audio, video, text). Studies that rely on quantifying media content for their analyses use, for example, visibility (how often political actors appear in the media) or tonality (how they are evaluated). Other studies examine the topics discussed or the language used in the media, in order to identify whether political actors are able to place their own policy positions in the media. Leading studies from economic literature, for example, examine how often a newspaper quotes the same think tanks (Groseclose and Milyo (2005), Lott and Hassett (2014)) or uses the same language (Gentzkow and Shapiro 2004) as members of Congress. Following this approach, the present paper compares topics discussed in media outlets with topics addressed in the press releases of the parties in the German “Bundestag”, to measure the content similarity between online news and parties press releases.¹ To discover the latent topics in the corpus of text data, the structural topic model (STM) developed by M. E. Roberts, Stewart, and Airoldi (2016) is applied. This probabilistic text model results in a probability distribution for each document across all topics, which is then aggregated to calculate the degree of difference between the news articles of different media providers and the press releases of the parties using a linear regression model.

Literature review

Newspaper articles and their metadata, such as publisher and publication date have been subject of investigation in economic research.

Background information

The political situation in Germany (June 2017 - March 2018)

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

¹For the sake of simplicity, both news articles and press releases will be referred to as documents in the following.

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 2017.² 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.

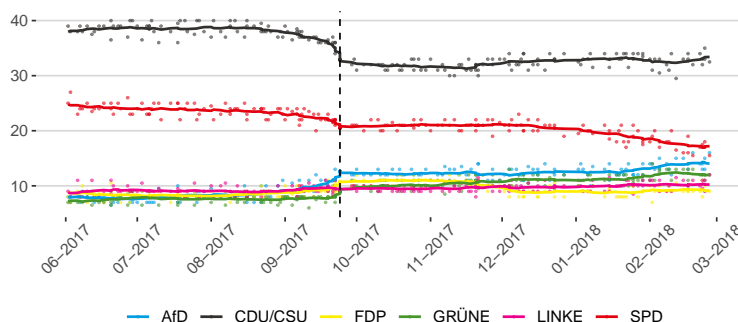


Figure 1: Election polls during the period under review

German online news market

The analysis performed in this paper is based on the news articles of the following news websites: *Bild.de*, *DIE WELT*, *FOCUS ONLINE*, *Handelsblatt*, *SPIEGEL ONLINE*, *stern.de*, *ZEIT ONLINE*. As can be seen from Figure 2(a), except for *Handelsblatt* (position 53), these media outlets are among the top 30 German online news providers in the period under review in terms of visits.³

The main source of income for these privately managed media houses is digital advertising, even though paid content is playing an increasingly important role. However, according to a survey on digital news by the Reuters Institute (Newman et al. 2018) only 8% of respondents pay for online news. The online survey for German data was undertaken between 19th - 22nd January 2018 by the Hans Bredow Institute⁴ with a total sample size of 2038 adults (aged 18+) who access news once a month or more. Among other questions, participants were asked which news sources they use to access news online.⁵ The results displayed in Figure 2(b) indicate that the media used for the analysis play a relevant role in their consumption.

²For each party the survey results of the seven major institutes are considered. To calculate a smooth line for each party on each day, the moving average within 15 days (7 before the day, 7 after the day, and the day itself) is estimated. The data source is <https://www.wahlrecht.de/>.

³The term visit is used to describe the call to a website by a visitor. The visit begins as soon as a user generates a page impression (PI) within an offer and each additional PI, which the user generates within the offer, belongs to this visit.

⁴<https://www.hans-bredow-institut.de/de/projekte/reuters-institute-digital-news-survey>

⁵The exact question was: “Which of the following brands have you used to access news online in the last week (via websites,

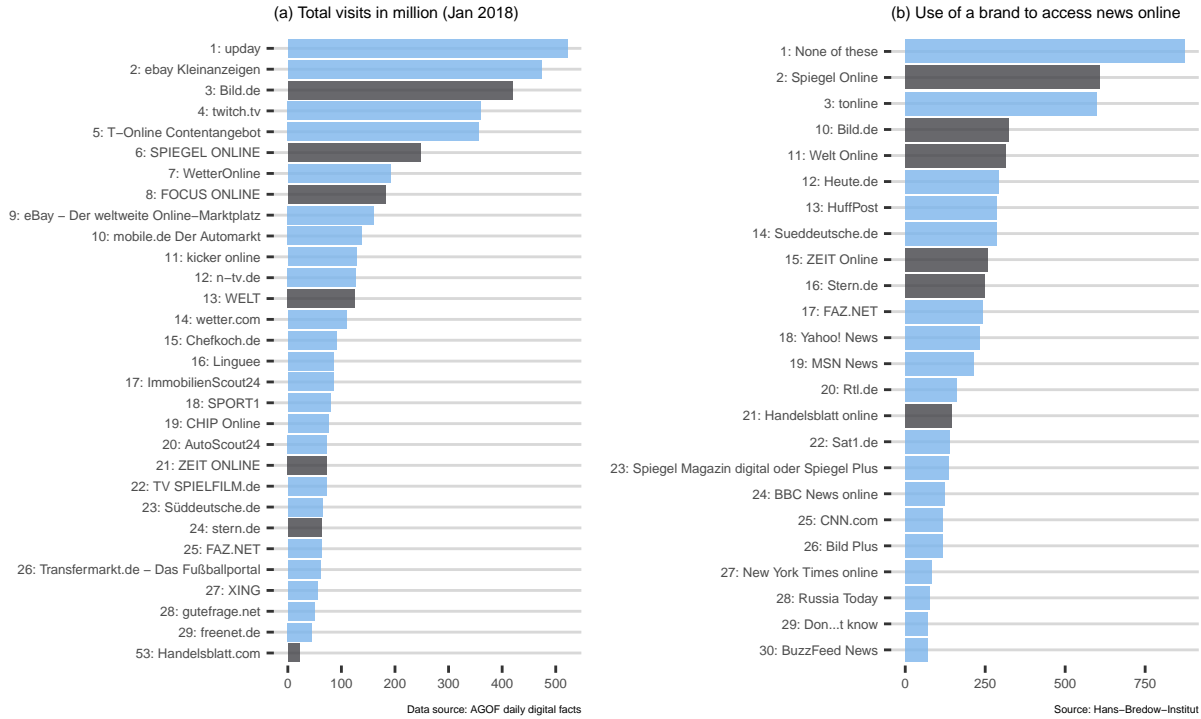


Figure 2: Selected German news brands

Data

I conduct the estimation on a sample of 16,473 online news articles from the seven German news providers mentioned in the previous section⁶ about domestic politics and press releases of the seven parties that have been in the Bundestag since the 2017 federal elections⁷. Both news articles and press releases are dated from June 1, 2017 to March 1, 2018.

News articles scraped from the Webhose.io API.⁸ In order to consider only news about national politics, the articles were filtered based on their URL.

Figure 3 shows the distribution of the number of articles by date and media outlet. 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).⁹ Furthermore, Figure 3 shows that *DIE WELT* published the most articles on domestic policy, followed by *stern.de*, *Handelsblatt* and *FOCUS ONLINE*.

The press releases were scraped from the public websites of the political parties and parliamentary groups using an automated script written in *Python*.¹⁰

Looking at the boxplots of text length (Figure 5), it becomes evident that:¹¹

- mean and median text length of news articles is higher than in press releases

apps, social media, and other forms of Internet access)? Please select all that apply.”

⁶ *Bild.de*, *DIE WELT*, *FOCUS ONLINE*, *SPIEGEL ONLINE*, *stern.de*, *ZEIT ONLINE*, *Handelsblatt*

⁷ CDU, SPD, B90/Grüne, FDP, AfD, Die Linke

⁸ For more information see <https://docs.webhose.io/reference#about-webhose>. The scraping code was written in Python and can be made available on request.

⁹ The peak in July especially for *stern.de* is due to increased reporting about the G20 summit in Hamburg.

¹⁰ The scraping code was written in Python and can be made available on request.

¹¹ See Table 8 for an overview of the summary statistics.

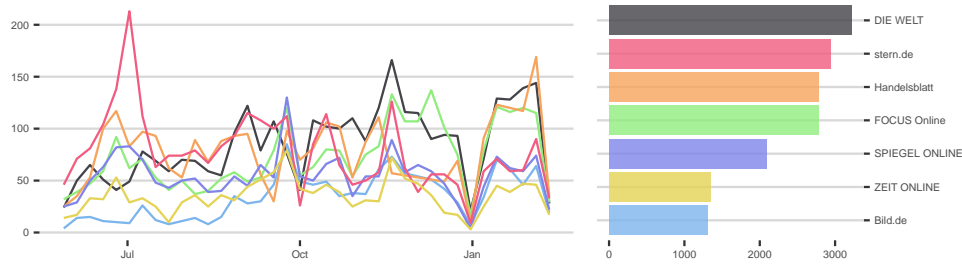


Figure 3: Distribution of news articles

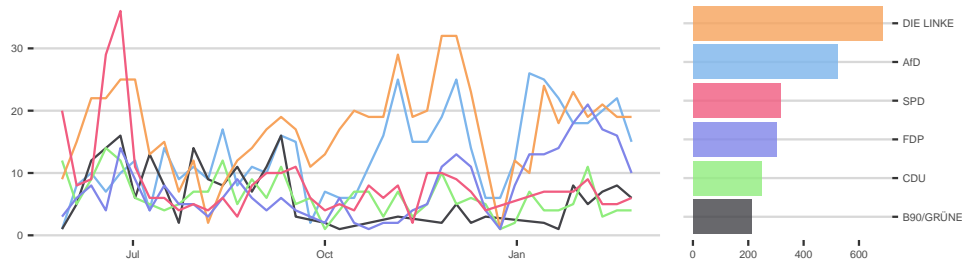


Figure 4: Distribution of press releases

- *Handelsblatt* published new articles with the highest median text length (488) followed by *ZEIT ONLINE* (459), however *DIE WELT* has the article with the highest word count (14.507).
- press releases of CDU have the highest median (256), but also the highest standard dev. (106). press releases of FDP have the lowest median (144).

Data preparation

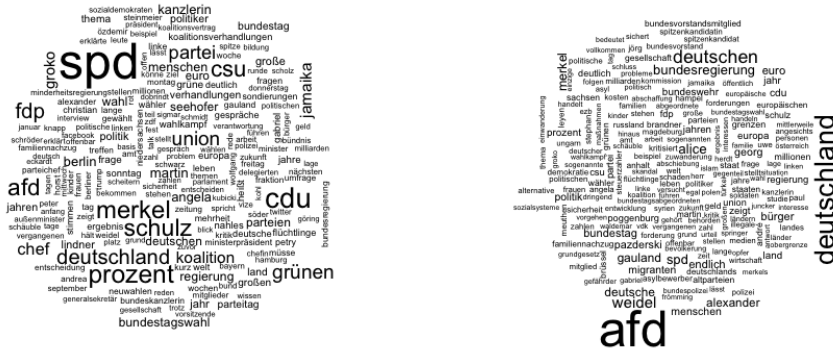
To use text as data for statistical analysis, different pre-processing steps have to be conducted. In fact, in order to use text as data and reduce the dimensionality to avoid unnecessary computational complexity and overfitting, pre-processing the text is a central task in text mining (Gentzkow, Kelly, and Taddy 2017, @bholat_text_2015). Intuitively the term frequency (tf) of a word is a measure of how important that word may be for the understanding of the text. To visualize these terms, word clouds are a commonly used technique in text mining as they translate the tf into the size of the term in the cloud. As can be seen in ??, problems arise with words that are highly frequent. For example “die”, or “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, Kelly, and Taddy 2017), are important to the grammatical structure of a text, but typically don’t add any additional meaning and can therefore be neglected.

To remove distorting words, the pre-defined stop word list from the Snowball project¹² is used together with a customized, domain-specific list of stop-words. Additionally punctuation character (e.g. ., ,, !, ?, etc.) and all numbers are removed from the data. A next step to reduce the dimensionality of text data is to apply an adequate stemming technique. 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.¹³

¹²<http://snowball.tartarus.org/algorithms/german/stop.txt>

¹³<https://tartarus.org/martin/PorterStemmer/>

As an example, the following word clouds represent the most frequent words of the pre-processed articles for *Bild.de* (left word cloud) and press releases of AfD (right word cloud). It becomes evident that these are texts discussing domestic policy issues. The SPD in particular seems to be highly frequent for *Bild.de*.



The next step is to divide the entire data set into individual documents and to represent these documents as a finite list of unique terms. In this setting, each news article and each press release represents a document d , whereby each of these documents can be assigned to a news website or a party. The sum of all documents forms what is called the corpus. For each document $d \in \{1, \dots, D\}$ 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 $v \in \{1, \dots, V\}$ and where V is the number of unique terms. The $D \times V$ matrix \mathbf{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. Table 1 provides a sample output of the document-term matrix used in this paper, where each document is represented by a unique id (the row name in the example below). This representation is often referred to as the bag of words model (Gentzkow, Kelly, and Taddy 2017), since the order in which words are used within a document is disregarded.

Table 1: Document-term matrix - sample values

| | beginn | etablierten | dublin | gewordenen | versucht | brand | besitzen |
|-------|--------|-------------|--------|------------|----------|-------|----------|
| 12909 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 8270 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 14797 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 4037 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 15251 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 974 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 5650 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 5850 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 17665 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 7568 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

Estimate topic similarity of documents

A structural topic model to identify the latent topics

To discover the latent topics in the corpus of press releases and news articles, a structural topic modeling (STM) developed by (M. E. Roberts, Stewart, and Airoldi 2016) is applied. 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. The STM developed by (M. E. Roberts, Stewart, and Airoldi 2016) is a recent extension of the standard topic modelling technique, labeled as latent Dirichlet allocation (LDA), which refers to the Bayesian model in (Blei, Ng, and Jordan 2003) that treats each word in a topic and each topic in a document

as generated from a Dirichlet - distributed prior.¹⁴

The underlying idea for these models suggests that each individual topic k 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.

The STM is an extension of the LDA process since it allows covariates of interest (such as the publication date of a document or it’s author) to be included in the prior distributions for both topic proportions (θ) and topic-word distributions (ϕ). This way, STM offers a method of ‘structuring’ the prior distributions in the topic model, including additional information in the statistical inference procedure, while LDA assumes that $\theta \sim \text{Dirichlet}(\alpha)$ and $\phi \sim \text{Dirichlet}(\beta)$, where α and β are fitted with the model.

In order to include the covariates in the statistical inference procedure, two design matrices of covariates (X and Z) are specified, where each row defines a vector of covariates for a specific document. In X , the covariates for topic prevalence are given, so that the probability of a topic for each document varies according to X , rather than resulting from a single common prior. The same applies to Z , in which the covariates for the word distribution within a topic are specified. The underlying data generating process to generate each individual word $w_{d,n}$ in a document d for the n^{th} word-position can be described as follows:

- for each document i , draw its distribution of topics θ_d depending on the metadata included in the model defined in X ;
- for each topic k , draw its distribution of words ϕ_k depending on the metadata included in the model defined in Z ;
- for each word n , draw its topic z_n based on θ_i ;
- for each word n , draw the term distribution for the selected topic $\phi_{z_{d,n}}$.

One crucial assumption to be made for topic models like LDA or STM is the number of topics (K) that occur over the entire corpus. There is not a “right” answer to the number of topics that are appropriate for a given corpus (Grimmer and Stewart 2013). (M. Roberts, Stewart, and Tingley 2016b) propose to measure topic quality through a combination of semantic coherence and exclusivity of words to topics. Semantic coherence is a criterion developed by (Mimno et al. 2011) and is closely related to pointwise mutual information (Newman et al. 2010): it is maximized when the most probable words in a given topic frequently co-occur together.

Using the function *searchK* from the *stm* package several automated tests are performed to help choose the number of topics including the average exclusivity and semantic coherence as well as the held out likelihood (Wallach, Mimno, and McCallum 2009) and the residuals (Taddy 2012). This process revealed that a model with 40 topics best reflects the structure in the corpus. Furthermore, I use the author and bi-week dummies of a document as topical prevalence variable. In other words, I assume that the probability of a topic to be included in a news article or a press release depends on the author of that document and when it was published. I argue that these variables are best suited to capture temporal and publisher level variation in the documents.

In general inference of mixed-membership models, such as the one applied in this paper, has been a thread of research in applied statistics (Blei, Ng, and Jordan 2003, @erosheva_mixed-membership_2004, @braun_variational_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 and the covariates influencing the prior distributions). 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, 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, Kelly, and Taddy 2017). These manual audits are applied together with numeric optimization based on the topic coherence measure suggested by (Mimno et al. 2011).

```
## stm(documents = news_df_sparse, K = 40, prevalence = ~source +
```

¹⁴See also Griffiths and Steyvers (2002), Griffiths and Steyvers (2004) and Hofmann (1999)


```
## s(year_biweek), data = covariates, init.type = "Spectral")
```

Results of the STM

The generative process of the STM results in a topic distribution θ_d for each document d over all topics k and a word distribution ϕ_k for each topic over all terms in the vocabulary. The most probable words of each topic may help to understand what each topic is about.¹⁵ However, since those most probable words are not necessarily the most exclusive words and they only represent a small fraction of the probability distribution, interpretation should be done very cautiously.

For our analysis, we use the topic distribution of each document. Figure 7 illustrates such a topic distribution of two news paper articles. The red numbers indicate the topic probability if it is greater than 0.02. News article 1¹⁶ shows a clear distribution towards topic 36 (0.89), for which terms like Bundeswehr, Soldaten (soldiers), Nato, Verteidigungsministerin (defense minister) are among the most probable words. News article 2¹⁷ does not show such a clear tendency towards a single topic. Topic 40 (0.34), 18 (0.24) and 5 (0.19) are within a comparable range. However, for all three topics similar terms are among the top terms.

Similarly as for the news articles, Figure 8 illustrates the topic distribution for two press releases randomly chosen from the corpus. For press release 1¹⁸ topic 24 is the most probable topic which contains terms about the G20 Summit, during which left-wing radicals caused considerable riots. Topic distribution of press article 2¹⁹ shows peaks for topic 6 (0.39) and 35 (0.28). Top terms of topic 6 contain the words trump, us, usa, deutschland (Germany) and präsident (president). Similarly topic 35 seems to deal with German foreign policy, since top terms include words like eu, deutschland (Germany), europa and bundesregierung (Federal Government).

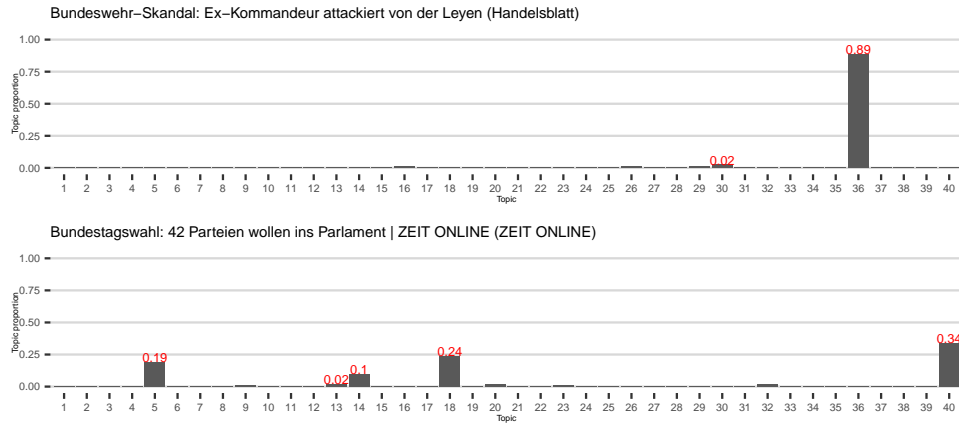


Figure 7: Topic probability of sample news articles

The left chart of Figure 9 displays the 15 topics with the highest probability for press releases of the AfD. The right side of the figure shows how the probability of two sample topics changes over the period under consideration compared to two sample news papers. It becomes clear, that topic 9²⁰ is systematically more likely in the AfD's press releases compared to the two newspapers. There is a noticeable increase in probability during the election campaign period and ends in a peak on election day itself. For Handelsblatt and Bild.de, too, a slight increase around election day is discernible and the probability of this topic shows some peaks for Bild.de both before and after the election. The top words of Theme 38²¹ suggest that it

¹⁵Table 9 gives an overview of the most probable terms for each topic.

¹⁶Bundeswehr scandal: ex-commander attacks Von Der Leyen

¹⁷Bundestag elections: 42 parties want to be elected to parliament.

¹⁸Lars Herrmann: The danger for Germany and its Basic Law is also coming from the left

¹⁹Trump chooses the path to isolation

²⁰Topic 9: afd, party, saxony, gauland, parties, pazderski, hocke

²¹Topic 38: refugees, germany, people, number, refugees, family reunion, year

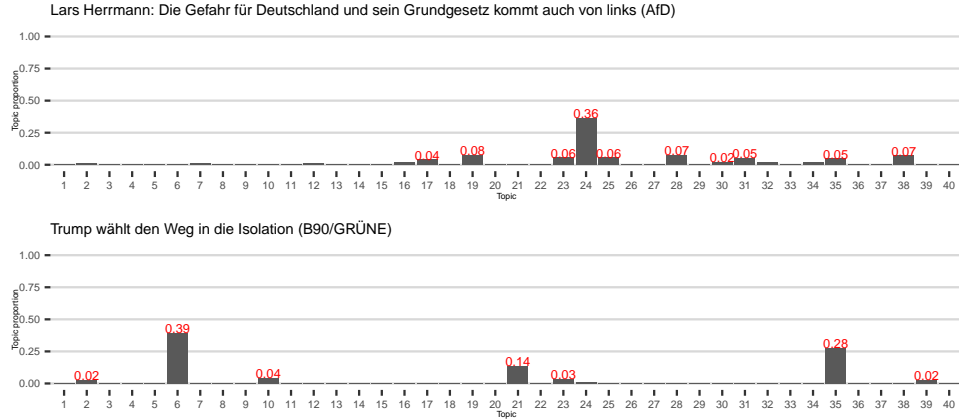


Figure 8: Topic probability of sample press releases

addresses refugees - a topic the AfD has a very clear position on. The probability of this topic increases in the AfD's press releases until about a month before the election and then levels off somewhat. A similar trend can be seen for the news articles from Bild.de. The curve from Handelsblatt is rather flat and shows no apparent difference between before and after the election.

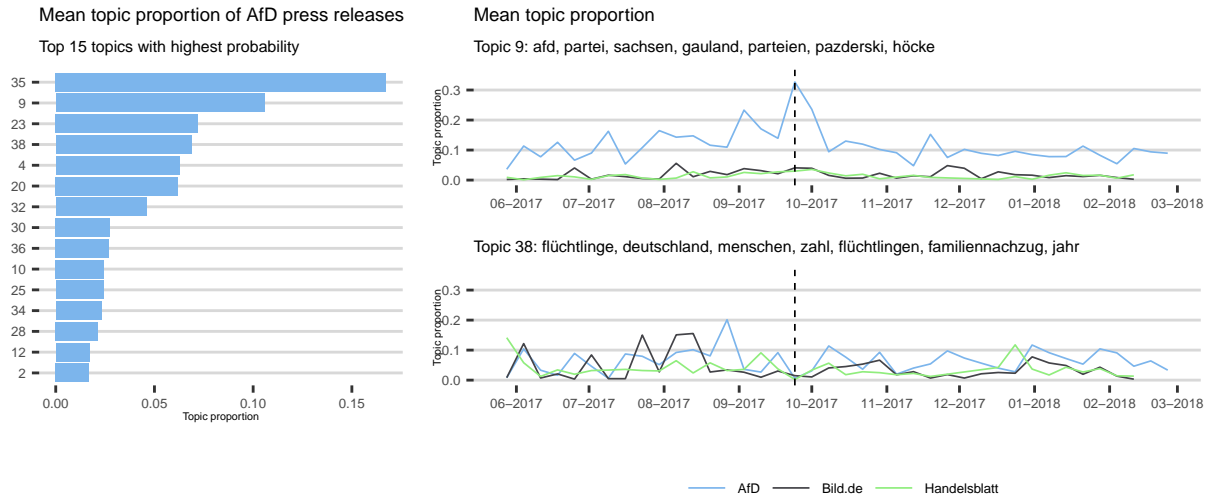


Figure 9: Comparison of topic probability - sample topics

Document Cosine similarity

Next, the cosine similarity measure is used in order to compare the retrieved topic distribution of documents. Cosine similarity is a measure for the distance between two vectors and is defined between zero and one; values towards 1 indicate similarity. As topic proportions per document are vectors of the same length, the cosine similarity allows a comparison of the topic distribution between two documents.²²

²²For applications of cosine similarity to compare of topic model outcomes see e.g. Rehs (2020) and Ramage, Dumais, and Liebling (2010)

$$\text{cosine similarity} = \cos(\theta) = \frac{a * b}{||a|| ||b||}$$

For example, [Table 2](#) displays the most similar documents of the document with the title *Glyphosat-Streit vergiftet GroKo-Verhandlungen: Was wusste Merkel?* (*Bild.de*).

Table 2: Most similar documents

| title | source | cos_sim |
|---|-----------|---------|
| Alice Weidel: Undemokratisches Ausgrenzen der AfD schadet dem Amt des Bundespräsidenten | AFD | 0.729 |
| Fakten müssen für Zulassung von Pflanzenschutzmitteln maßgeblich sein | FDP | 0.474 |
| Dialog mit Russland garantiert Sicherheit in Europa | DIE LINKE | 0.415 |
| Keine Verlängerung für Glyphosatanwendung | SPD | 0.31 |
| Georg Pazderski: Rotrotgrün auf Bundesebene keine Option | AFD | 0.163 |

In the next step, for each news paper, the cosine similarity between all topic-document distribution pairs between the news papers articles and the press releases is calculated if that press releases was published within 7 days before the publication date of the news article. This means the topic distribution of news article 1 is compared to press release 1, 2, 3 and so on as long as the press release was published within 7 days before the news article.

- See [Table 3](#) for an example illustration of the data for *DIE WELT*

Table 3: Dataset structure step 1 - DIE WELT

| title1 | title2 | cosine_sim | source1 | source2 | date1 | date2 |
|-----------------------|----------------------|------------|----------|-----------|------------|------------|
| Union und SPD ein... | Antisemitismus j... | 0.05 | DIE WELT | CDU | 2018-02-01 | 2018-01-26 |
| Umfrage unter Flüc... | Georg Pazderski: ... | 0.03 | DIE WELT | AFD | 2018-01-24 | 2018-01-22 |
| Parlamentarische ... | Den Konflikt um K... | 0.45 | DIE WELT | DIE LINKE | 2017-11-01 | 2017-11-01 |
| Messerangreifer v... | Wichtiges Urteil ... | 0.05 | DIE WELT | SPD | 2017-11-10 | 2017-11-08 |
| *Beschimpfte mich... | André Poggenburg:... | 0.03 | DIE WELT | AFD | 2017-12-04 | 2017-11-29 |

Next, the mean cosine similarity for each news article publication date (date1) and party (source2) is estimated to obtain the final data frame (see [Table 4](#)).

Table 4: Final dataset structure - DIE WELT

| date1 | source1 | source2 | cos_sim |
|------------|----------|-----------|---------|
| 2017-07-24 | DIE WELT | AFD | 0.28 |
| 2017-07-08 | DIE WELT | B90/GRÜNE | 0.16 |
| 2017-08-28 | DIE WELT | CDU | 0.2 |
| 2017-07-21 | DIE WELT | FDP | 0.18 |
| 2017-07-20 | DIE WELT | B90/GRÜNE | 0.17 |

Model estimations

To get a first idea of the trend of the data over time, the mean cosine similarity between the news articles and each parties press releases conditional on the day can be plotted. [Figure 10](#) shows that kind of plot for *Handelsblatt* and *Bild.de* (See [Figure 12](#) for all news papers)

Observations:

- at the beginning, most news papers (except for *Handelsblatt*) have the highest similarity with the AfD.
- this similarity is diminishing over the course of time. However, for *DIE WELT* & *FOCUS ONLINE* it is still the highest at the end of the time span.
- *stern.de*, *Bild.de*, *ZEIT ONLINE* & *SPIEGEL ONLINE*: Similarity with AfD is lower at the end of the time period

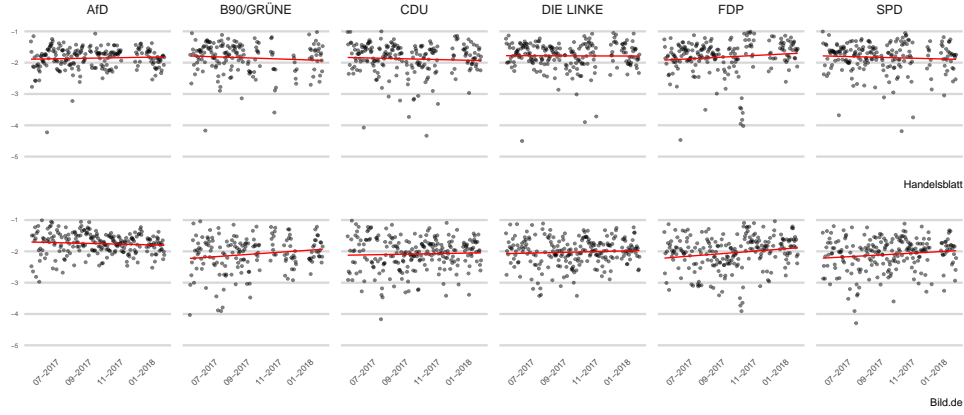


Figure 10: Log of daily mean cosine similarity between newspaper/press articles pairs

OLS dummy regression

- for each news publisher, a simple OLS regression is estimated, where the similarity score ($\ln(CS_i)$) on day i between the news articles of that news paper and the press releases of a political party k is the dependent variable and the political party dummies are the independent variables.

$$\ln(CS_i) = \beta_0 + \beta_n D_{i,k-1} + \epsilon_i$$

- i = date (date1), k = political party (source2)

Table 5: Results from the OLS model

| | Dependent variable: | | | | | | |
|-------------------------|--------------------------|-------------------------|-------------------------|----------------------|--------------------------|--------------------------|--------------------------|
| | DIE WELT | stern.de | ZEIT ONLINE | Handelsblatt | FOCUS Online | Bild.de | SPIEGEL ONLINE |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| source2B90/GRÜNE | -0.232*** (0.036) | -0.237*** (0.045) | -0.220*** (0.057) | 0.033 (0.050) | -0.297*** (0.038) | -0.319*** (0.055) | -0.202*** (0.045) |
| source2CDU | -0.274*** (0.033) | -0.207*** (0.042) | -0.280*** (0.053) | -0.003 (0.047) | -0.300*** (0.036) | -0.347*** (0.051) | -0.240*** (0.043) |
| source2DIE LINKE | -0.268*** (0.033) | -0.140*** (0.042) | -0.197*** (0.053) | 0.078* (0.047) | -0.290*** (0.036) | -0.272*** (0.051) | -0.208*** (0.042) |
| source2FDP | -0.247*** (0.033) | -0.139*** (0.042) | -0.201*** (0.053) | 0.080* (0.047) | -0.281*** (0.036) | -0.292*** (0.051) | -0.221*** (0.043) |
| source2SPD | -0.263*** (0.034) | -0.180*** (0.042) | -0.228*** (0.054) | 0.026 (0.048) | -0.301*** (0.036) | -0.337*** (0.051) | -0.267*** (0.043) |
| Constant | -1.765*** (0.024) | -1.991*** (0.030) | -1.764*** (0.038) | -1.856*** (0.033) | -1.831*** (0.025) | -1.746*** (0.036) | -1.878*** (0.030) |
| Observations | 1.372 | 1.378 | 1.404 | 1.206 | 1.428 | 1.321 | 1.424 |
| R ² | 0.069 | 0.027 | 0.023 | 0.005 | 0.072 | 0.047 | 0.035 |
| Adjusted R ² | 0.065 | 0.023 | 0.019 | 0.001 | 0.069 | 0.044 | 0.031 |
| Residual Std. Error | 0.365 (df = 1366) | 0.458 (df = 1372) | 0.589 (df = 1398) | 0.484 (df = 1200) | 0.401 (df = 1422) | 0.549 (df = 1315) | 0.473 (df = 1418) |
| F Statistic | 20.144*** (df = 5; 1366) | 7.532*** (df = 5; 1372) | 6.540*** (df = 5; 1398) | 1.188 (df = 5; 1200) | 22.193*** (df = 5; 1422) | 13.048*** (df = 5; 1315) | 10.136*** (df = 5; 1418) |

Note:

*p<0.1; **p<0.05; ***p<0.01

Interpretation (see Table 5)

When D_k switches from 0 (AfD) to 1 (party k), the % impact of D on Y can be estimated as $\exp(\beta) - 1$

Example (B90/GRÜNE):

```
## source2B90/GRÜNE
## -0.2067046
```

- Compared to AfD, the similarity of topics of *DIE WELT* and B90/GRÜNE is 20% lower.

In general, for all news papers (except for *Handelsblatt*) the topic similarity is significantly less between the news articles of that news paper and press releases of political parties (compared to AfD).

Regression discontinuity model

- We assume that the topic similarity changes after the election day
- See [Figure 13](#) for all news papers

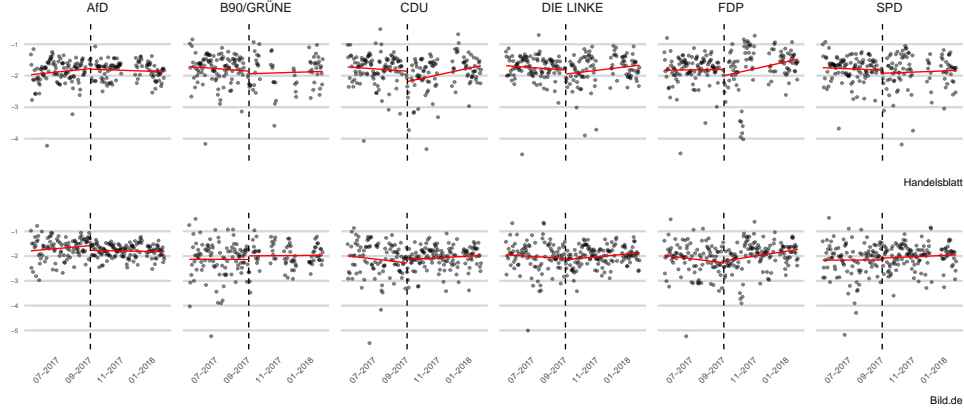


Figure 11: Log of mean cosine similarity between newspaper/press articles pairs - with cutoff value

- Initially introduced by Thistlethwaite and Campbell (1960) & formalized by Hahn, Todd, and Van der Klaauw (2001)
- It's a rigorous nonexperimental approach used to estimate treatment effects, where treatment is determined by whether an observed assignment variable (aka “forcing” or “running” variable) exceeds a known cutoff point.
- In our model, the running variable W is the time difference between date i and the election date (in days) and the cutoff point c is the election day
- The idea of regression discontinuity design is to use observations with a W_i close to c for the estimation of β_1
- β_1 is the average treatment effect for observations with $W_i = c$ which is assumed to be a good approximation to the overall treatment effect.
- In other words, β_1 gives us the average change of the similarity between the content of news articles and press releases after the election day
- Including interaction terms $T_i D_{n_j}$ allows us to estimate the treatment effect for each party \rightarrow since we are estimating an isolated model for each newspaper, we have the average treatment effect of the election day for each newspaper/party pair.

Calculate a regression discontinuity model for each news paper.

$$\ln(\text{CS}_i) = \beta_0 + \beta_1 T_i + \beta_2 W_i + \beta_3 D_{i,k-1} + \beta_4 T_i D_{i,k-1} + \epsilon_i$$

where

$$\begin{aligned} T_i &= 1 \text{ if date } \geq \text{election date} \\ T_i &= 0 \text{ if date } < \text{election date} \end{aligned}$$

so that the receipt of treatment T_i is determined by the threshold c (election day) of the continuous (running) variable W_i .

The interaction term $T_i D_{i,k-1}$ means that the slope can vary on either side of the treatment threshold for each party.

- The coefficient β_1 is how the intercept jumps (the RDD effect). Since we are controlling for each party, the coefficient shows the treatment effect on the AfD.
- β_4 is how the slope changes for each party.

Table 6: Results from the regression discontinuity model

| | Dependent variable: | | | | | | |
|------------------------------|---------------------------|--------------------------|---------------------------|--|---------------------------|--------------------------|--------------------------|
| | DIE WELT (1) | stern.de (2) | ZEIT ONLINE (3) | Cosine similarity of topic distribution Handelsblatt (4) | FOCUS Online (5) | Bild.de (6) | SPIEGEL ONLINE (7) |
| treated | -0.149** (0.058) | -0.090 (0.073) | -0.113 (0.089) | -0.089 (0.081) | -0.100 (0.062) | -0.189** (0.087) | 0.047 (0.073) |
| X_centered | 0.0002 (0.0003) | 0.001*** (0.0003) | -0.001** (0.0004) | 0.001*** (0.0004) | 0.0003 (0.0003) | 0.001 (0.0004) | -0.0003 (0.0003) |
| source2B90/GRÜNE | -0.267*** (0.048) | -0.216*** (0.060) | -0.180** (0.077) | 0.105 (0.066) | -0.338*** (0.053) | -0.445*** (0.078) | -0.187*** (0.062) |
| source2CDU | -0.259*** (0.048) | -0.115* (0.060) | -0.232*** (0.077) | 0.098 (0.066) | -0.288*** (0.053) | -0.450*** (0.078) | -0.170*** (0.062) |
| source2DIE LINKE | -0.251*** (0.048) | -0.109* (0.060) | -0.160** (0.077) | 0.134** (0.066) | -0.270*** (0.053) | -0.342*** (0.078) | -0.156** (0.062) |
| source2FDP | -0.291*** (0.048) | -0.195*** (0.060) | -0.201*** (0.077) | 0.069 (0.066) | -0.355*** (0.053) | -0.441*** (0.078) | -0.292*** (0.062) |
| source2SPD | -0.278*** (0.048) | -0.143** (0.060) | -0.201*** (0.077) | 0.098 (0.066) | -0.339*** (0.053) | -0.479*** (0.078) | -0.266*** (0.062) |
| treatedTRUE:source2B90/GRÜNE | 0.050 (0.071) | -0.042 (0.089) | -0.154 (0.112) | -0.184* (0.102) | 0.078 (0.077) | 0.245** (0.110) | -0.031 (0.091) |
| treatedTRUE:source2CDU | -0.030 (0.066) | -0.175** (0.083) | -0.090 (0.104) | -0.204** (0.094) | -0.022 (0.072) | 0.178* (0.103) | -0.131 (0.085) |
| treatedTRUE:source2DIE LINKE | -0.032 (0.066) | -0.059 (0.083) | -0.068 (0.104) | -0.113 (0.094) | -0.037 (0.072) | 0.120 (0.103) | -0.097 (0.085) |
| treatedTRUE:source2FDP | 0.084 (0.066) | 0.109 (0.083) | -0.002 (0.104) | 0.024 (0.094) | 0.137* (0.072) | 0.260** (0.103) | 0.134 (0.085) |
| treatedTRUE:source2SPD | 0.025 (0.067) | -0.068 (0.084) | -0.058 (0.105) | -0.145 (0.095) | 0.070 (0.072) | 0.252** (0.104) | -0.002 (0.086) |
| Constant | -1.689*** (0.037) | -1.956*** (0.047) | -1.692*** (0.059) | -1.816*** (0.051) | -1.780*** (0.041) | -1.647*** (0.059) | -1.900*** (0.048) |
| Observations | 1,372 | 1,378 | 1,404 | 1,206 | 1,428 | 1,321 | 1,424 |
| R ² | 0.091 | 0.045 | 0.080 | 0.023 | 0.080 | 0.059 | 0.043 |
| Adjusted R ² | 0.083 | 0.037 | 0.072 | 0.013 | 0.072 | 0.050 | 0.035 |
| Residual Std. Error | 0.361 (df = 1359) | 0.455 (df = 1365) | 0.573 (df = 1391) | 0.481 (df = 1193) | 0.401 (df = 1415) | 0.547 (df = 1308) | 0.472 (df = 1411) |
| F Statistic | 11.334*** (df = 12; 1359) | 5.354*** (df = 12; 1365) | 10.113*** (df = 12; 1391) | 2.335*** (df = 12; 1193) | 10.240*** (df = 12; 1415) | 6.847*** (df = 12; 1308) | 5.310*** (df = 12; 1411) |

Note:

*p<0.1; **p<0.05; ***p<0.01

Example interpretation for *Bild.de* (see Table 6)

The coefficient β_4 for $D_{SPD} = 1$ shows the difference of the treatment effect for SPD. To illustrate this, we can compare the model equation for $D_{SPD} = 1$ and $D_{SPD} = 0$

$$D_{SPD} = 1: \begin{aligned} \ln(\text{CS})(D_{SPD} = 1) &= -1.647 + (-0.189)T + (0.001)W - 0.479 + (0.252)T \\ \ln(\text{CS})(D_{SPD} = 1) &= -2,126 + (0.001)W + (0.252 - 0.189)T \end{aligned}$$

$$D_{SPD} = 0: \begin{aligned} \ln(\text{CS})(D_{SPD} = 0) &= -1.647 + (-0.189)T + (0.001)W \\ \ln(\text{CS})(D_{SPD} = 0) &= -1.647 + (0.001)W + (-0.189)T \end{aligned}$$

- When D_{SPD} switches from 0 to 1, the treatment effect increases by 0.252.

To interpret this coefficient, we have to transform it (our dependent variable is log transformed).

For $D_{SPD} = 0$: $\exp(-0.189) - 1 = -0.172$

After the election day the topic similarity between *Bild.de* and AfD decreased by ~17.2%

$D_{SPD} = 1$: $\exp(-0.189 + 0.252) - 1 = 0.065$

After the election day the topic similarity between *Bild.de* and SPD increased by ~6.5% compared to AfD.

General interpretation:

- News articles of *DIE WELT* and *Bild.de* show a significant decrease of topic similarity with AfD after the election. No such effect can be found for the other news papers.

- News articles of *Handelsblatt* are significantly less similar with B90/G & CDU after the election (compared to AfD). The opposite is true for *Bild.de* where new articles are more similar to ALL party press releases (except for DIE LINKE) when compared to AfD.

The results show, that for some news papers (*DIE WELT* & *Bild.de*), there is a significant change in the topic similarity between their news articles and the press releases of parties.

Discussion and conclusion

This paper investigates whether political reporting of news papers is similar for all political parties. Results show, that the news articles of all news papers (except for *Handelsblatt*) are significantly more similar to press releases of the AfD than any other party.

Furthermore, it was assumed, that this reporting differs between periods of election campaign. The results show a significant effect of the switch between “before” election (election campaign period) and “after” election for some news papers.

- For *DIE WELT* and *Bild.de* the election date has a significant effect on the similarity with the AfD: The similarity between news articles and press releases of AfD decreases

Annex

Table 7: Online sources for press releases

| | Party | Parliamentary Group |
|----------------|--------------|---|
| CDU | cdu.de | presseportal.de |
| SPD | spd.de | spdfraktion.de |
| FDP | fdp.de | fdpbt.de |
| B90/Die Grünen | gruene.de | gruene-bundestag.de |
| DIE LINKE | die-linke.de | die-linke.de/start/presse/aus-dem-bundestag |
| AfD | afd.de | afdbundestag.de |

Table 8: Summary statistics of text length

| source | n | mean | sd | median | min | max |
|----------------|------|--------|--------|--------|-----|-------|
| AfD | 523 | 212.83 | 72.16 | 196 | 103 | 553 |
| B90/GRÜNE | 211 | 229.32 | 63.37 | 219 | 104 | 399 |
| Bild.de | 1303 | 476.07 | 318.28 | 398 | 121 | 3710 |
| CDU | 248 | 274.54 | 106.08 | 256 | 100 | 1030 |
| DIE LINKE | 686 | 200.47 | 71.78 | 190 | 101 | 1048 |
| DIE WELT | 3222 | 509.57 | 612.06 | 380 | 121 | 14507 |
| FDP | 301 | 161.9 | 83.78 | 144 | 100 | 999 |
| FOCUS Online | 2780 | 393.89 | 317.05 | 297.5 | 121 | 5647 |
| Handelsblatt | 2785 | 589.51 | 495.82 | 488 | 121 | 6899 |
| SPD | 315 | 213.41 | 56.16 | 208 | 103 | 429 |
| SPIEGEL ONLINE | 2089 | 539.09 | 415.05 | 413 | 121 | 3466 |
| stern.de | 2943 | 514.66 | 616.55 | 373 | 121 | 9287 |
| ZEIT ONLINE | 1351 | 513.75 | 387.14 | 459 | 121 | 8015 |

% Table created by stargazer v.5.2.2 by Marek Hlavac, Harvard University. E-mail: hlavac at fas.harvard.edu
 % Date and time: Sun, Mar 28, 2021 - 14:10:13

Table 9: 7 most probable terms per topic

| | Top Terms |
|----|--|
| 1 | a, the, s, of, u, brexit, großbritannien |
| 2 | merkel, angela, kanzlerin, bundeskanzlerin, cdu, merkels, deutschland |
| 3 | spd, union, cdu, csu, koalitionsvertrag, koalitionsverhandlungen, schulz |
| 4 | afd, weidel, gauland, alice, alexander, politiker, äusserungen |
| 5 | stimmen, wahlkreis, kandidaten, afd, wahl, gewählt, fdp |
| 6 | trump, us, usa, deutschland, präsident, donald, berlin |
| 7 | cdu, union, peter, politiker, spahn, altmaier, schäuble |
| 8 | spd, koalition, union, groko, große, koalitionsverhandlungen, parteitag |
| 9 | afd, partei, sachsen, gauland, parteien, pazderski, hocke |
| 10 | diesel, unternehmen, deutschland, autos, deutschen, industrie, fahrverbote |
| 11 | ge, ten, be, le, ver, lambsdorff, te |
| 12 | gericht, prozess, urteil, richter, staatsanwaltschaft, verfahren, jahre |
| 13 | berlin, deutschen, osten, o, tag, jahr, millionen |
| 14 | august, cdu, spd, prozent, bundestagswahl, wahl, parteien |
| 15 | kohl, helmut, kohls, einheit, kanzler, tod, deutschen |
| 16 | spd, nahles, andrea, partei, scholz, schulz, schwesig |
| 17 | csu, seehofer, horst, söder, obergrenze, bayern, chef |
| 18 | prozent, umfrage, spd, union, fdp, cdu, afd |
| 19 | polizei, stadt, menschen, polizisten, täter, verletzt, angaben |
| 20 | euro, milliarden, jahr, millionen, prozent, bund, geld |
| 21 | grünen, linke, linken, özdemir, partei, wagenknecht, göring |
| 22 | cdu, niedersachsen, spd, grünen, rot, fdp, landtag |
| 23 | welt, politik, menschen, jahren, lange, frage, fragen |
| 24 | g, hamburg, gipfel, polizei, hamburger, demonstranten, scholz |
| 25 | deutschland, is, verfassungsschutz, syrien, gefährder, islamisten, staat |
| 26 | steinmeier, schmidt, russland, frank, bundespräsident, glyphosat, walter |
| 27 | afd, petry, partei, fraktion, frauhe, meuthen, gauland |
| 28 | berliner, berlin, amri, maizière, innenminister, behörden, daten |
| 29 | gabriel, sigmar, außenminister, spd, schröder, amt, gerhard |
| 30 | bundestag, spd, abgeordneten, abgeordnete, parlament, abstimmung, fraktion |
| 31 | türkei, erdoğan, türkischen, deutschland, bundesregierung, türkische, deutsche |
| 32 | frauen, deutschland, kinder, studie, eltern, muslimen, antisemitismus |
| 33 | fdp, jamaika, lindner, koalition, neuwahlen, spd, grünen |
| 34 | facebook, maas, twitter, gesetz, internet, netz, heiko |
| 35 | eu, deutschland, europa, bundesregierung, europäischen, deutschen, menschen |
| 36 | bundeswehr, soldaten, leyn, nato, ursula, einsatz, verteidigungsministerin |
| 37 | schulz, spd, martin, kanzlerkandidat, wahlkampf, bundestagswahl, partei |
| 38 | flüchtlinge, deutschland, menschen, zahl, flüchtlingen, familiennachzug, jahr |
| 39 | fdp, grünen, jamaika, csu, union, grüne, cdu |
| 40 | bundestagswahl, afd, wahl, prozent, partei, bundestag, parteien |

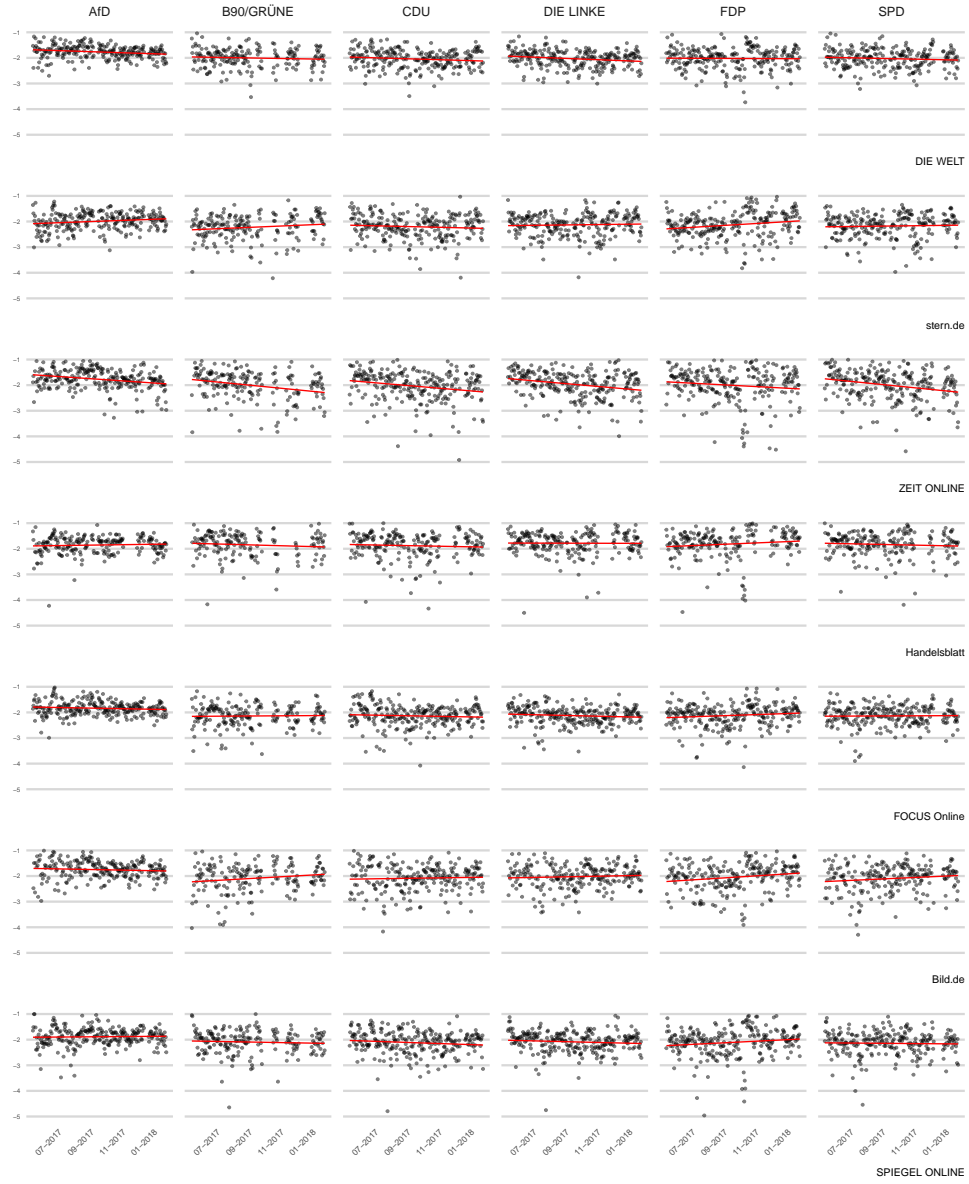


Figure 12: Log of daily mean cosine similarity between newspaper/press articles pairs

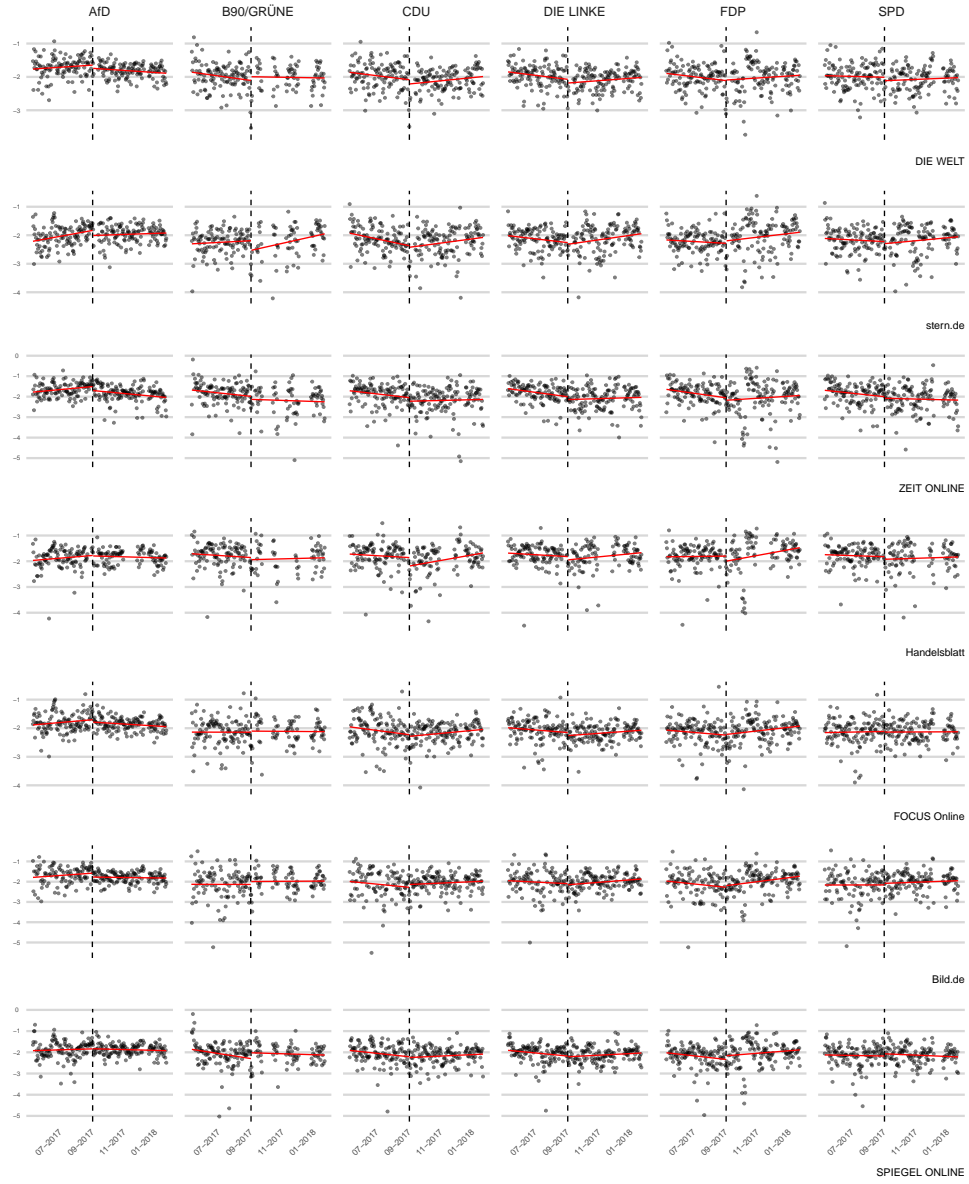


Figure 13: Log of daily mean cosine similarity between newspaper/press articles pairs - with cutoff value

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