Biased reporting by the German media?

An Analysis of Political News Coverage in Germany for the 2017 Bundestag Election

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I 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 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 supports the allegation of biased media reporting, especially during election campaigns.

For advertising-financed media, the battle for the recipients' attention 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. As a result, consumers pay a non-monetary price providing their attention, which the media platform bundles and sells to advertising customers. This business model corresponds to that of a platform market. Media companies act as platforms that connect the advertising market 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 media and communication studies (Takens et al. 2013). The debate about media logic is embedded in a broader discussion about the interaction between the press, politics, and the public. The underlying thesis is that political news content produces news values and narrative techniques that media use to attract

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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) state 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. Blassnig et al. (2019) show that populist key messages by political and media actors in news articles provoke more reader comments under these articles. Therefore, media competing for readers' attention have an incentive to pick up on the key messages of these parties. These, in turn, benefit from being able to place their agendas in the public debate (Druckman and Parkin (2005), Eberl (2018)). It is assumed that smaller, non-established parties benefit from placing their topics in the media to get them into the tods. 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. Instead, this paper intends to measure how online news coverage coincides with the messaging of different political parties. Especially during election campaigns, political parties want the media agenda to be congruent with their agenda to define the issue-based criteria on which voters will evaluate them (Eberl, Boomgaarden, and Wagner 2017). Parties instrumentalize their public relations to highlight issues they perceive as competent on, that they "own," and essential to their voters (Kepplinger and Maurer 2004). This paper, therefore, analyzes the content of political news in the period before and after the 2017 federal elections in Germany to determine a) the extent to which these news echo topics covered by the parties during the election campaign, b) whether there is a difference between the parties, and c) how and if topic similarity changes after the election.

To answer these and other media-related questions in the political context, quantifying media content is a prerequisite. One of the critical challenges is determining the features used to describe media content - audio, video, or text content. Studies that rely on quantifying media content for their analyses use, for example, visibility (how often political actors appear in the media (Lengauer and Johann 2013)) or tonality (how they are evaluated (Eberl, Boomgaarden, and Wagner 2017)). Other studies examine the topics discussed or the language used in the media to identify whether political actors can place their 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 (M. A. 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 parties' press releases in the German "Bundestag" to measure the content similarity between these documents.[1] The structural topic model (STM) developed by M. E. Roberts, Stewart, and Airoldi (2016) is applied to discover the latent topics in the corpus of text data. This probabilistic text model results in a probability distribution for each document across

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

all topics, which is then aggregated to calculate the degree of difference between the news articles of different media providers and the parties' press releases.

The following Section II Background information provides background information on Germany's political situation and the German online news market during the period under consideration.

II 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 crucial 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)[2], 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 profile. In reporting on the federal elections, leading party members of the AfD and party supporters repeatedly accused the mass media of reporting unilaterally and intentionally presenting the AfD badly.

After the election, forming 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/GRÜNE (Bündnis 90/Die Grünen, green party)). The SPD initially rejected the grand coalition. However, 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/GRÜNE 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, the media discussed possible re-election or a minority government as alternatives before the SPD decided to hold coalition talks with the CDU/CSU. This step provoked significant resistance from the party base, which called for a party-internal referendum on a grand coalition. However, after the party members voted in favor of the grand coalition, CDU/CSU and SPD formed a government 171 days after the federal elections.

[2]CDU/CSU, Union and CDU are used as synonyms in this paper for simplicity.

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.

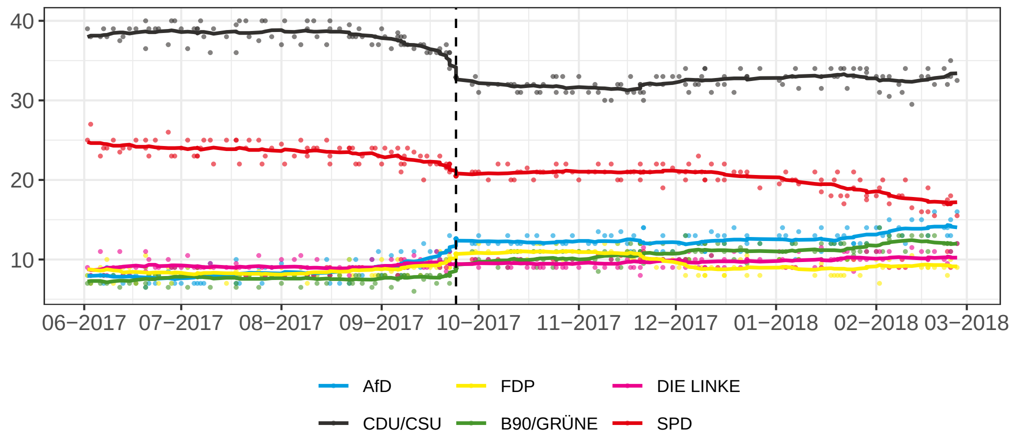
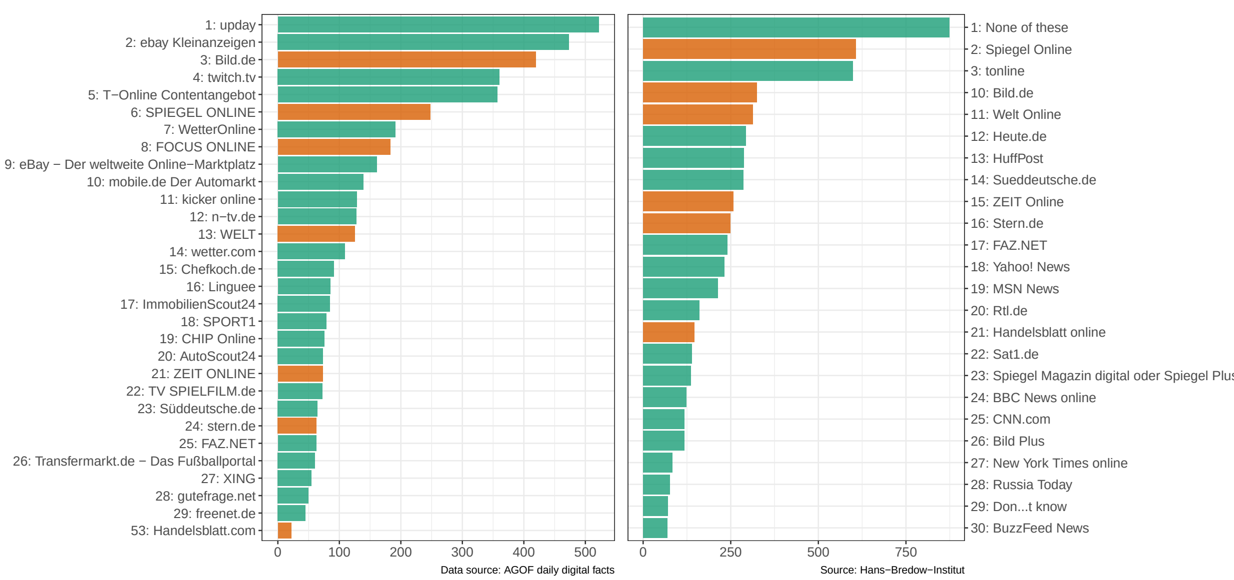


Figure 1: Election polls during the period under review

German online news market



(a) Total visits in million (Jan 2018)

(b) Use of a brand to access news online

Figure 2: Selected german news brands

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 shown in 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 primary source of income for these privately managed media houses is digital advertising, even though paid content plays an increasingly important role. However, according to a survey on digital news by the Reuters Institute (N. 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 Institute[4] 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.

III Empirical analysis

The empirical strategy used in this paper leverages the structure of the topic model framework, specifically the Structural Topic Model (STM), to generate topic distributions for each document which are then used to measure similarity between documents. The diagram below outlines the approach in more detail. Section III describes the data sources and how text data is processed to obtain a multi-dimensional space, where each dimension corresponds to a word in the document. Subsequently, section IV uses this so-called document-term matrix as input to calculate each document's topic distribution using an STM. This, in turn, leads to a reduction in dimensionality in that each document is now represented as a distribution over the topics. These document-topic vectors are then used to calculate the cosine similarity between two documents. The final Section uses this similarity measure as a dependent variable in a regression model with different specifications.

Text data as input for statistical modelling

I conduct the estimation on a sample of 18,757 online news articles from the seven German news providers described in the previous section[6] about domestic politics and press releases of the seven parties that have been in the Bundestag since the 2017 federal elections[7]. Both news articles and press releases are dated from June 1, 2017 to March 1, 2018.

News articles were scraped from the Webhose.io API.[8] To consider only news about national politics, the articles were filtered based on their URL. The press releases were scraped from the public websites of the political parties and parliamentary groups using an automated script.[9]

[3] The 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

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

[9] The scraping code was written in R and can be made available on request.

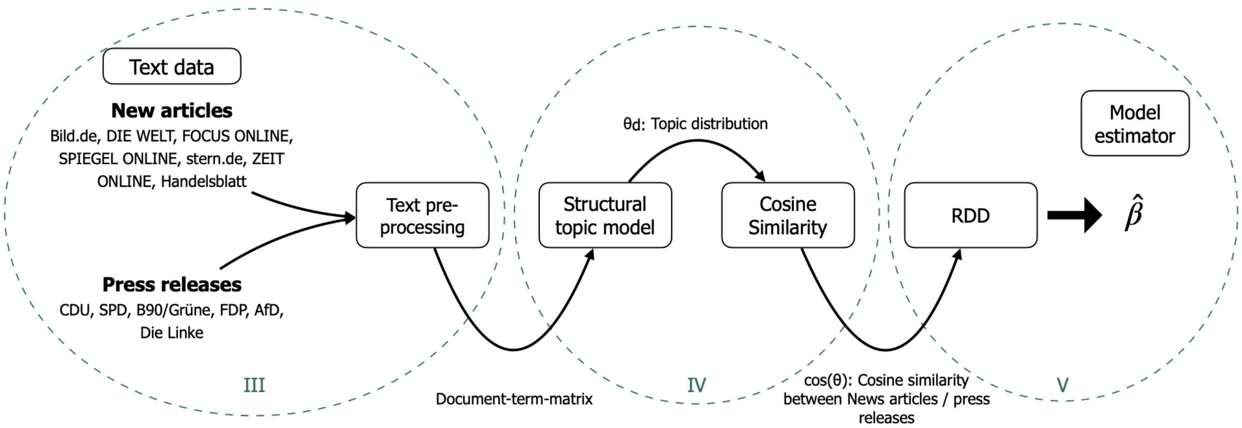


Figure 3: High level overview

Figure 4 shows the distribution of the number of articles by date and media outlet. There is a high peak around the federal elections on September 24 and another one shortly after the failure of the Jamaica coalition talks on November 19 (indicated by the red dotted lines).[10] Furthermore, Figure 4 shows that DIE WELT published the most articles on domestic policy, followed by stern.de, Handelsblatt and FOCUS ONLINE.

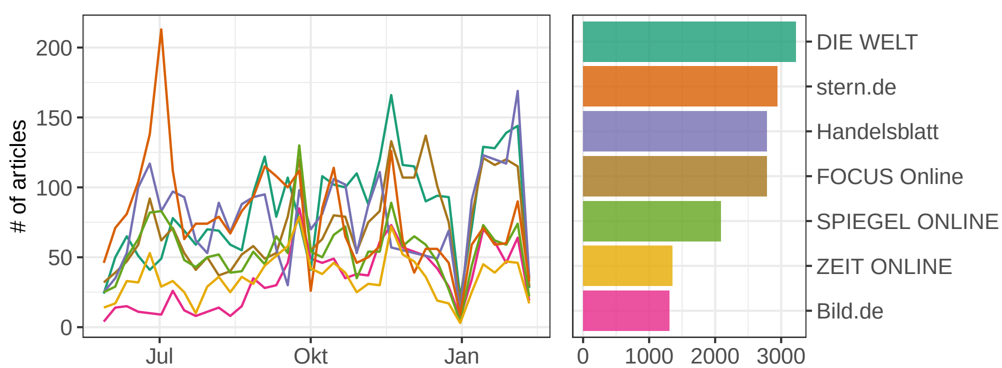


Figure 4: Distribution of news articles

[10]The peak in July especially for stern.de is due to increased reporting about the G20 summit in Hamburg.

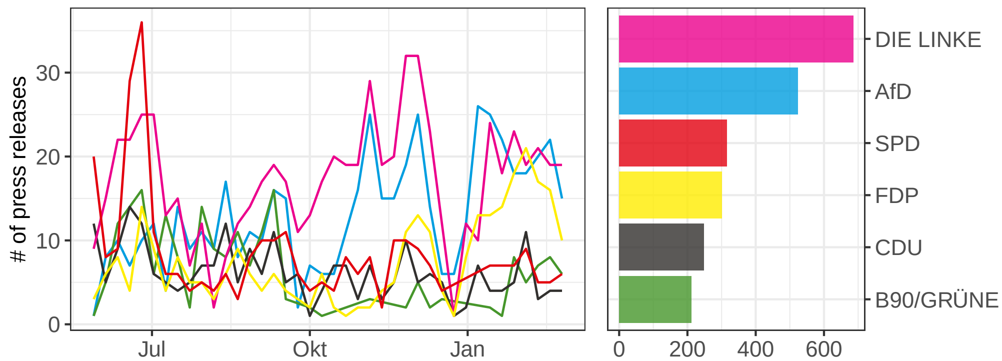


Figure 5: Distribution of press releases

Table 1: Summary statistics of word counts

source	n	mean	sd	median	min	max
News articles						
Bild.de	1303	476.07	318.28	398.0	121	3710
DIE WELT	3222	509.57	612.06	380.0	121	14507
FOCUS Online	2780	393.89	317.05	297.5	121	5647
Handelsblatt	2785	589.51	495.82	488.0	121	6899
SPIEGEL ONLINE	2089	539.09	415.05	413.0	121	3466
stern.de	2943	514.66	616.55	373.0	121	9287
ZEIT ONLINE	1351	513.75	387.14	459.0	121	8015
Press releases						
AfD	523	212.83	72.16	196.0	103	553
B90/GRÜNE	211	229.32	63.37	219.0	104	399
CDU	248	274.54	106.08	256.0	100	1030
DIE LINKE	686	200.47	71.78	190.0	101	1048
FDP	301	161.90	83.78	144.0	100	999
SPD	315	213.41	56.16	208.0	103	429

Table 1 illustrates that, on average, news articles have a higher word count than the parties' press releases. While for news articles, the average is between 394 (FOCUS Online) and 590 (Handelsblatt), with press releases, the range is between 162 (FDP) and 275 (CDU). DIE WELT published the article with the most words (14.507) - the most extended press release has 1.048 words published by DIE LINKE.

Several processing steps have to be performed to make the text quantifiable to use text as data input for statistical analyses. 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 (M. Gentzkow, Kelly, and Taddy (2017), Bholat et al. (2015)). Intuitively, the term frequency (tf) of a word measures how important that word may be for understanding the text. Word clouds are a commonly used visualization technique in text mining as they translate the tf into the size of the term in the cloud.

Words like "die," or "der" (eng. "the"), "and" (eng. "and"), and "ist" (eng. "is") are extremely common but unrelated to the quantity of interest. Often called stop words (M. Gentzkow, Kelly, and Taddy 2017), these terms are essential to the grammatical structure but typically do not add any additional meaning and can be neglected. The predefined stop word list from the Snowball project[11] is used together with a customized, domain-specific list of words to identify and remove these distorting words. Additionally, punctuation characters (e.g. ., !, ?) and all numbers are removed from the data. The 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 based on a set of shortening rules applied to a word until it has a minimum number of syllables.[12]

As an example, the following word clouds represent the most frequent words of the pre-processed articles for Bild.de (Figure 6(a)) and press releases of AfD (Figure 6(b)). Thus, it becomes evident that these are texts discussing domestic policy issues. The SPD, in particular, seems to be highly frequent for Bild.de.

(a) Bild

(b) AfD

Figure 6: Wordcloud after pre-processing

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. Next, 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, and each entry counts the occurrences of a unique term in that document. Table 2 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

[11] http://snowball.tartarus.org/algorithms/german/stop.txt
[12] https://tartarus.org/martin/PorterStemmer/

often referred to as the bag of words model (M. Gentzkow, Kelly, and Taddy 2017) since it disregards the words' order within a document.

Table 2: Document-term matrix - sample values

	papers	nachzug	sex	stimmten	abgestürzt	gdp	autos
14317	0	0	0	0	0	0	0
851	0	0	0	0	0	0	0
96	0	0	0	0	0	0	0
2801	0	0	0	0	0	0	0
13257	0	0	0	0	0	0	0
14957	0	0	0	0	0	0	0
2308	0	0	0	0	0	0	0
3117	0	0	0	0	0	0	0
6357	0	0	0	1	0	0	0
18293	0	0	0	0	0	0	0

A structural topic model to identify the latent topics

Next, a structural topic modeling (STM) developed by (M. E. Roberts, Stewart, and Airoldi 2016) is applied to discover the latent topics in the corpus of press releases and news articles. 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 is an extension of the standard topic modeling 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.[13]

The underlying idea for these models suggests that each topic k potentially contains all of the unique terms within the vocabulary V with a different probability. Therefore, each topic k can be represented as a probability vector ϕ_k over all unique terms V. Simultaneously, each 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 its 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. At the same time, LDA assumes that θ Dirichlet(α) and ϕ Dirichlet(β), 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. X gives the covariates for topic prevalence resulting in each document's probability of a topic 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

[13]See also Griffiths and Steyvers (2002), Griffiths and Steyvers (2004) and Hofmann (1999)

are specified. Thus, the underlying data generating process to generate each word $w_{d,n}$ in 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 for topic models like LDA or STM is the number of topics (K) that occur over the entire corpus. Unfortunately, there is not a "right" answer to the number of appropriate topics 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). It is closely related to pointwise mutual information (D. Newman et al. 2010): it is maximized when the most probable words in a given topic are frequently used in a given topic co-occur together.

The function *searchK* from the *stm* package [stewart_bstewartstm_2021] supports the choice of the number of topics using several automated tests, including the average exclusivity and semantic coherence and 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, the author and bi-week dummies of a document are included as topical prevalence variables. In other words, I assume that the probability of a topic being included in a news article or a press release depends on the author and the publication date of that document. Therefore, 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 Braun and McAuliffe (2010). However, topic models are usually imprecise as the function to be optimized has multiple modes so 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 is impossible, I compute various models and compare their posterior probability to evaluate how results vary for different model specifications (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 (M. Gentzkow, Kelly, and Taddy 2017).

Results of the STM

As mentioned in the previous section, the generative process of the STM results in a topic distribution θ_d for each document 4d4 over all topics k and a word distribution ϕ_k for each topic over all terms in the vocabulary. Thus, the most probable words of each topic may help to understand the context of each topic.[14] However, since those most probable words are not

[14] Table 11 gives an overview of the most probable terms for each topic.

necessarily the most exclusive words and only represent a small fraction of the probability distribution, interpretation should be made cautiously.

For the analysis, the topic distribution of each document is used to estimate the similarity of documents. Figure 7 illustrates such a topic distribution of two newspaper articles. The red numbers display the topic probability (for probabilities>= 0.02). News article 1[15] shows a definite distribution towards topic 36, for which terms like Bundeswehr, Soldaten (soldiers), Nato, Verteidigungsministerin (defense minister) are among the most probable words. News article 2[16] does not show such a clear tendency towards a single topic. Topic 40, 18, and 5 are within a close range. However, for all three topics, similar terms are among the top terms.

Similarly, Figure 8 illustrates the topic distribution for two press releases randomly chosen from the corpus. For press release 1[17], topic 24 is the most probable, containing terms about the G20 Summit, during which left-wing radicals caused considerable riots. Topic distribution of press article 2[18] shows peaks for topics 6 and 35. The 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).

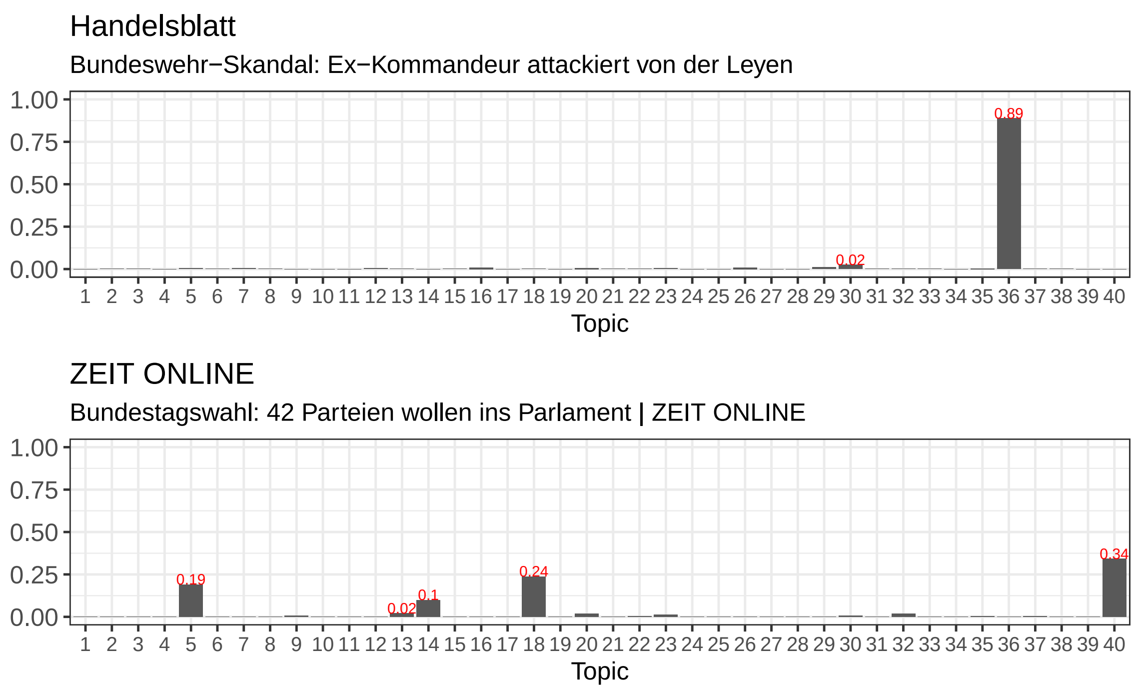


Figure 7: Topic probability of sample news articles

Since each document's source and publication date are known, the probability of specific topics can be analyzed, aggregated by this metadata. The left chart of Figure 9 shows the 15 topics with the highest probability for press releases published by the AfD. The right side of

[15] Bundeswehr scandal: ex-commander attacks Von Der Leyen
[16] Bundestag elections: 42 parties want to be elected to parliament.
[17] Lars Herrmann: The danger for Germany and its Basic Law is also coming from the left
[18] Trump chooses the path to isolation

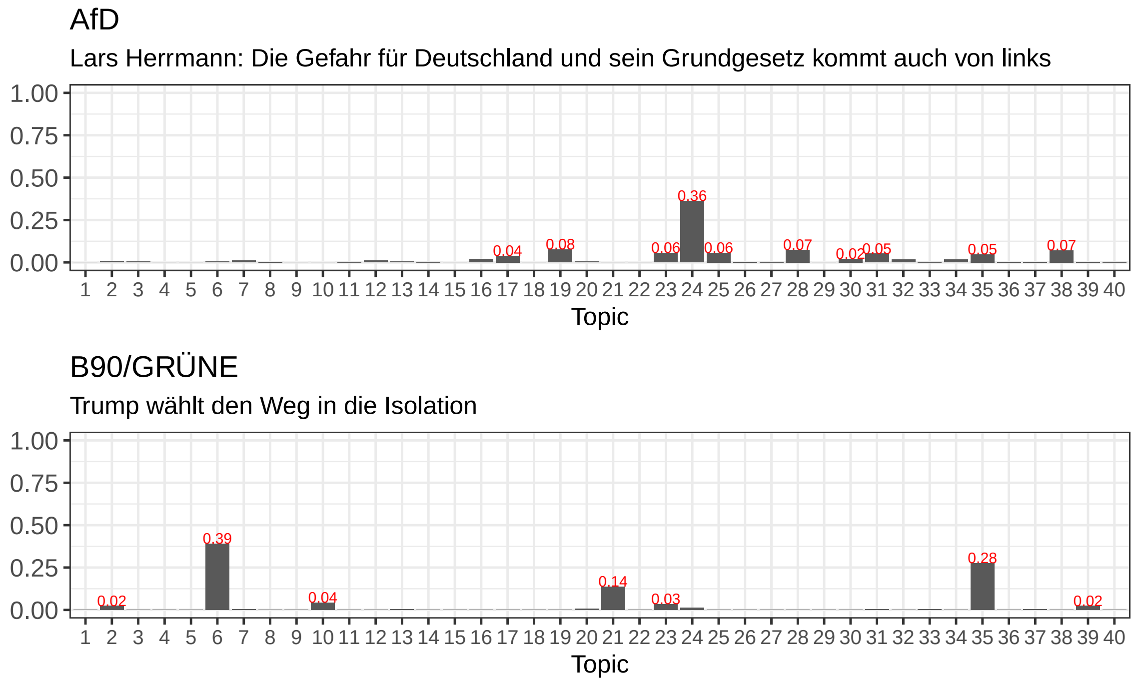


Figure 8: Topic probability of sample press releases

the figure aggregates the probability by source and time (in weeks) for two sample topics, displaying how they change over time in the AfD press releases compared to two sample newspapers. It becomes clear that topic 9[19] 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 and ends in a peak on election day itself. For Handelsblatt and Bild.de, too, a slight increase of probability around election day is discernible.

The top words of topic 38 suggest that it addresses refugees - a topic for which the AfD has an absolute position. 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 is discernible in the news articles from Bild.de. The curve from Handelsblatt is relatively flat and shows no apparent difference between before and after the election.

Figure 10 allows a similar analysis for the aggregated topic distribution in press releases of the FDP. The chart on the left illustrates that, as in the case of the AfD, topic 35 has the highest probability in the FDP press releases. Unlike in the case of the AfD, however, this is followed by topics with more evident temporal peaks, as shown on the right using two example topics. Topic 10[20] has a clear peak for both the newspapers and the FDP press releases around august 2017. There was a debate about whether and where driving bans for diesel cars would be introduced. After the states of Baden-Württemberg and North Rhine-Westphalia initially filed a lawsuit against this, the court proceedings that would decide whether driving bans are permissible began in mid-February 2018. The temporal curve of the FDP shows a further increase in topic probability at this time, which can also be detected at Handelsblatt. At

[19]translation: afd, party, saxony, gauland, parties, pazderski, höcke

[20]translation: diesel, enterprises, germany, cars, german, industry, driving bans

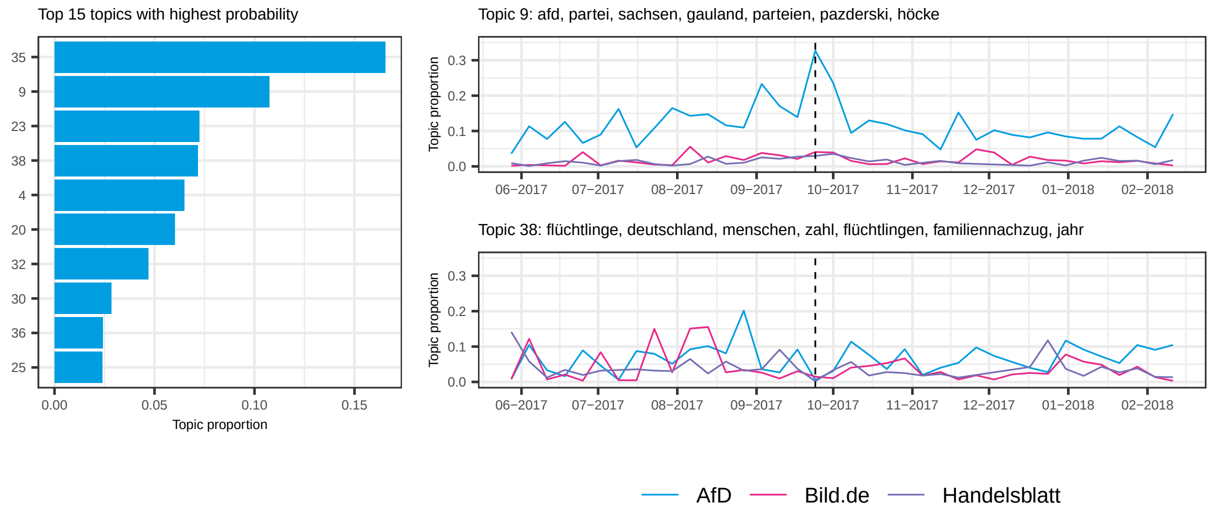


Figure 9: Comparison of topic probability - sample topics AfD

Bild.de, however, the topic is only taken up once briefly in August 2017, as only a very low topic probability can be seen after that.

The peak of the probability of topic 39[21] in all three sources right after the election reflects the exploratory talks on the possible formation of a Jamaica coalition, which officially failed on November 19, 2017, after the FDP announced its withdrawal from the negotiations.

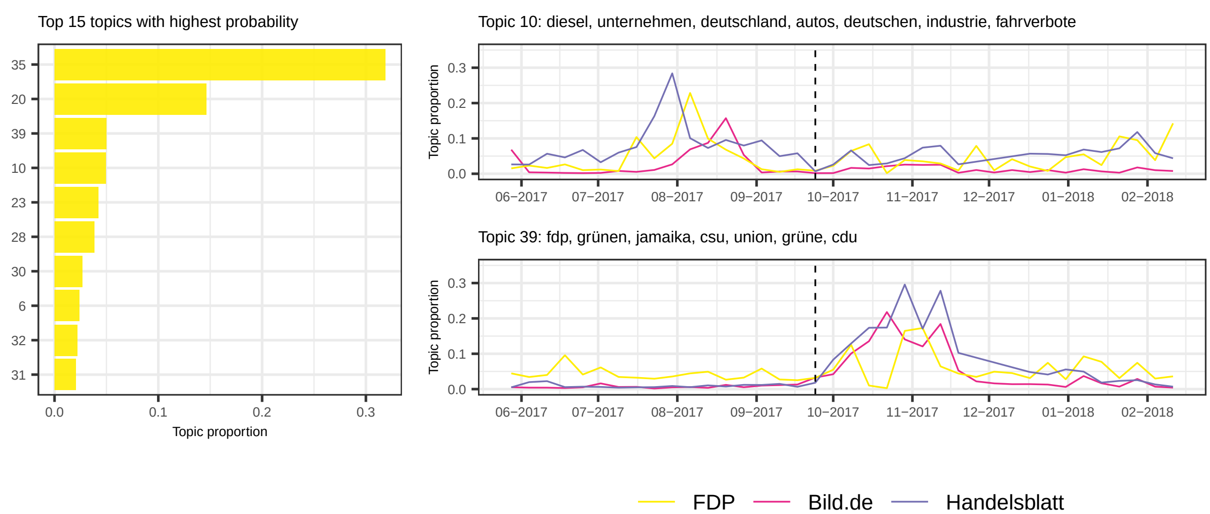


Figure 10: Comparison of topic probability - sample topics FDP

Similarity Measures

The topic distributions calculated by the STM are a vectorized representation of each document as represented by each row in the matrix in Table 3. Therefore, it is possible to

[21]translation: fdp, grünen, jamaika, cdu, union, grüne, cdu

calculate the similarity between two documents by estimating the cosine similarity between these vectors.[22]

Table 3: Document-topic distribution matrix

doc_index	1	2	3	4	5	6	..	40
1	0.0016	0.0453	0.0005	0.0078	0.0151	0.0118	...	0.4376
2	0.0041	0.0302	0.0003	0.0044	0.0007	0.2056	...	0.0006
3	0.0043	0.0039	0.0012	0.0003	0.0017	0.0266	...	0.0050
4	0.0016	0.0436	0.0006	0.0089	0.0095	0.0126	...	0.5181
5	0.0016	0.0515	0.0002	0.0122	0.0050	0.0121	...	0.5750

The cosine similarity is the cosine of the angle between two vectors projected in a multi-dimensional space and is defined between zero and one; values towards 1 indicate similarity. For example, the cosine similarity (CS) between document 1 and 2 for $K = 40$ topics can be calculated as follows.

$$\text{CS} = \cos(\vec{doc}_1, \vec{doc}_2) = \frac{\vec{doc}_1 * \vec{doc}_2}{||\vec{doc}_1||\vec{doc}_2||} = \frac{\sum_{i=1}^{K} \vec{doc}_{1,i}\vec{doc}_{2,i}}{\sqrt{\sum_{i=1}^{K} \vec{doc}_{1,i}^2}, \sqrt{\sum_{i=1}^{K} \vec{doc}_{2,i}^2}}$$

For each newspaper, the cosine similarity between all topic-document distribution pairs between the newspapers articles and the press releases is calculated if that press release was published within seven days before the publication date of the news article. Thus, the topic distribution of news article 1 is compared to press releases 1, 2, 3, and so on for press releases published within seven days before the news article. Table 4 illustrates a sample subset of the data for DIE WELT.

Table 4: Dataset structure step 1 - DIE WELT

title1	title2	cosine_sim	source1	source2	date1	date2
Bundestagswahl 20...	Alexander Gauland...	0.33	DIE WELT	AfD	2017-09-25	2017-09-19
WELT-Trend: Wird ...	Große Koalition ...	0.31	DIE WELT	FDP	2018-02-07	2018-02-05
Befangenheit fest...	Der Bundestag bes...	0.07	DIE WELT	SPD	2017-06-25	2017-06-23
Missbrauch in der...	Eine gerechte Fin...	0.01	DIE WELT	DIE LINKE	2017-07-19	2017-07-13
#CheckdieWahl: „W...	Paul Hampel: Dipl...	0.23	DIE WELT	AfD	2017-09-22	2017-09-22

Table 5[23] displays the most similar documents of the document with the title *Parteitag, Koalitions-Krimi, Ur-Wahl - Woran kann die GroKo jetzt noch scheitern? (Bild.de).*[24]

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

[23]Translations: 1) Asylum figures 2017 - black-red (synonym for GroKo) introduces upper limit through the back door (DIE LINKE) 2) Jörg Meuthen: Not a new GroKo, but LoKo - Loser Coalition (AfD) 3) Pension plans of Union and SPD worse than expected (FDP) 4) Union and SPD stabilize the extreme social injustice in this country (DIE LINKE) 5) Jürgen Pohl: Union and SPD agree on policy at the expense of pensioners and East Germans (AfD)

[24]Translation: Party conference, coalition thriller, primal election - what can fail the GroKo now? (Bild.de)

Table 5: Most similar documents

title	source	cos_sim
Asylzahlen 2017 - schwarz-rot führt Obergrenze durch die Hintertür ein	DIE LINKE	0.542
Jörg Meuthen: Nicht neue GroKo, sondern LoKo – Loser Koalition	AfD	0.522
Rentenpläne von Union und SPD schlimmer als erwartet	FDP	0.478
Union und SPD stabilisieren die krasse soziale Ungerechtigkeit in diesem Land	DIE LINKE	0.401
Jürgen Pohl: Union und SPD verabreden Politik zu Lasten von Rentnern und Ostdeutschen	AfD	0.388

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 6).

Table 6: Final dataset structure - DIE WELT

date1	source1	source2	cos_sim
2017-10-24	DIE WELT	SPD	0.09
2017-06-03	DIE WELT	DIE LINKE	0.21
2017-10-09	DIE WELT	DIE LINKE	0.13
2017-11-30	DIE WELT	SPD	0.08
2018-01-14	DIE WELT	CDU	0.13

OLS dummy regression

Finally, cosine similarity can be used as the independent variable in different model specifications to answer the research questions of this paper: (a) whether the topics addressed by the parties during the campaign are echoed in online news, (b) whether there is a difference for parties, and (c) how and whether topic similarity changes after the election. First, in OLS dummy regression, a OLS model with party dummies is computed for the pre-election period to examine the extent to which the news outlets pick up on the parties' issues during election campaigns. Then, in Regression discontinuity model, a regression discontinuity is specified to test whether the election day affected overall topic similarity.

To measure whether there is a significant difference in the topic similarity for each party for a news publisher, a simple OLS regression is estimated, where the similarity score ($\ln(\mathrm{CS}_t)$) on day t between the news articles of that news publisher and the press releases of a political party k is the dependent variable and the political party dummies are the independent variables.

$$\ln(\mathrm{CS}_t) = \beta_0 + \beta_n D_{t,k-1} + \epsilon_t,$$

with t = date[25], k = political party[26]

[25] date1 in Table 6

[26] source2 in Table 6

OLS dummy results

The columns in Table 7 report the results for each new publisher.[27] Since the dependent variable is log-transformed, the % impact of D on Y can be estimated using $exp(\hat{\beta}) - 1$. E.g., since the transformed coefficient for $D_{B90/GRÜNE}$ in the first column - representing the model for DIE WELT - is -0.279, a switch from 0 to 1 can be interpreted as a 36.4% decrease of topic similarity for B90/GRÜNE compared to AfD (the base dummy group), holding everything else equal. In other words: Compared to AfD, the similarity of topics of DIE WELT and B90/GRÜNE is 36.4% lower. Figure 11 plots the transformed coefficients for all newspaper/party pairs (insignificant coefficients are shown with low opacity). In general, for all newspapers - except for Handelsblatt - the topic similarity is significantly less between the news articles of that newspaper and press releases of political parties compared to press releases of the AfD. The most evident difference for all parties exists for Bild.de, followed by FOCUS ONLINE and DIE WELT. In the case of Handelsblatt no significant difference can be found for CDU/CSU, B90/GRÜNE and SPD (compared to AfD). However, the positive coefficients of DIE LINKE indicate that the topics discussed in press releases of that party and the articles of Handelsblatt are significantly similar compared to the press releases of the AfD.

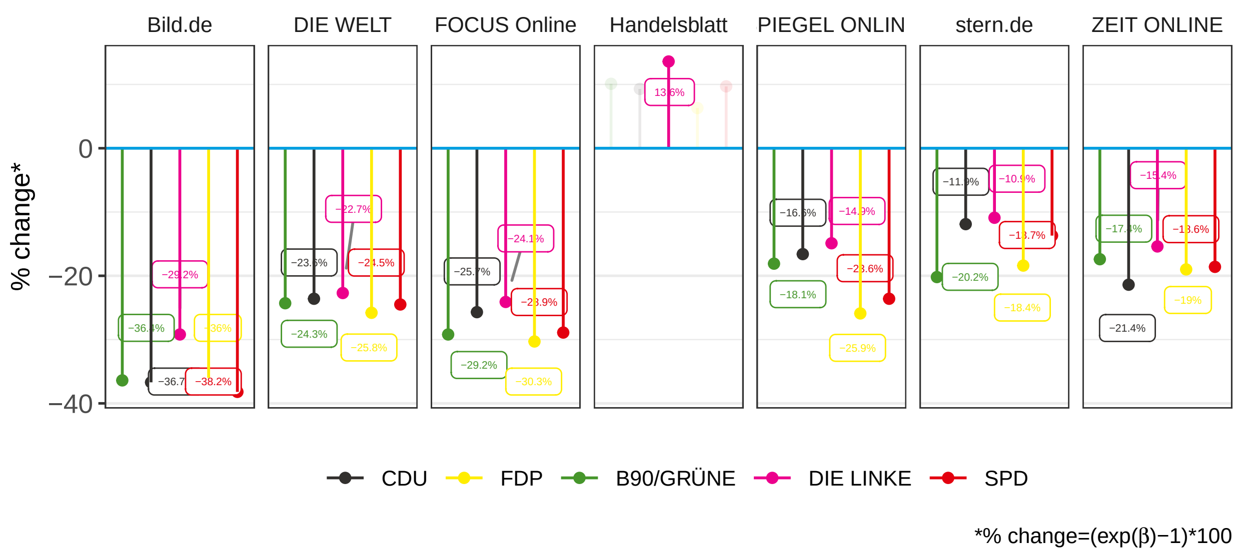


Figure 11: Coefficients of OLS dummy regression

Regression discontinuity model

I assume that news publishers report differently during election campaigns and that the election day introduces a change in the reporting. The underlying dynamic of this assumption coincides with the basic idea of regression discontinuity design (RDD). Therefore, an RDD is applied to identify the short-term effect of the election on the topic similarity between newspaper articles and press releases. The RDD was designed by Thistlethwaite and Campbell (1960) and formalized by Hahn, Todd, and Van der Klaauw (2001) to measure the effect of a treatment

[27] All regression output tables are created using Hlavac (2018)

Table 7: Results from the OLS dummy regression

	Dependent variable:						
	Cosine similarity of topic distribution						
	DIE WELT	stern.de	ZEIT ONLINE	Handelsblatt	FOCUS Online	Bild.de	SPIEGEL ONLINE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
B90/GRÜNE	-0.279^{***}	-0.226^{***}	-0.192^{***}	0.096	-0.345^{***}	-0.452^{***}	-0.199^{***}
	(0.050)	(0.054)	(0.065)	(0.061)	(0.058)	(0.093)	(0.067)
CDU	-0.270^{***}	-0.127^{**}	-0.241^{***}	0.089	-0.297^{***}	-0.457^{***}	-0.181^{***}
	(0.050)	(0.053)	(0.065)	(0.060)	(0.058)	(0.093)	(0.067)
DIE LINKE	-0.257^{***}	-0.116^{**}	-0.167^{**}	0.127^{**}	-0.275^{***}	-0.345^{***}	-0.162^{**}
	(0.050)	(0.053)	(0.065)	(0.060)	(0.058)	(0.093)	(0.067)
FDP	-0.299^{***}	-0.204^{***}	-0.210^{***}	0.061	-0.361^{***}	-0.446^{***}	-0.299^{***}
	(0.050)	(0.053)	(0.065)	(0.060)	(0.058)	(0.093)	(0.067)
SPD	-0.282^{***}	-0.147^{***}	-0.206^{***}	0.093	-0.341^{***}	-0.481^{***}	-0.270^{***}
	(0.050)	(0.053)	(0.065)	(0.060)	(0.058)	(0.093)	(0.067)
Constant	-1.705^{***}	-2.021^{***}	-1.641^{***}	-1.876^{***}	-1.793^{***}	-1.680^{***}	-1.880^{***}
	(0.036)	(0.038)	(0.046)	(0.043)	(0.041)	(0.066)	(0.048)
Observations	683	689	671	641	695	594	695
R^2	0.071	0.031	0.026	0.008	0.074	0.062	0.034
Adjusted R^2	0.064	0.024	0.019	0.0003	0.068	0.054	0.027
Residual Std. Error	0.379 (df = 677)	0.406 (df = 683)	0.485 (df = 665)	0.442 (df = 635)	0.440 (df = 689)	0.655 (df = 588)	0.512 (df = 689)
F Statistic	10.295^{***} (df = 5; 677)	4.436^{***} (df = 5; 683)	3.554^{***} (df = 5; 665)	1.038 (df = 5; 635)	11.089^{***} (df = 5; 689)	7.824^{***} (df = 5; 588)	4.890^{***} (df = 5; 689)
Note:							*p<0.1; **p<0.05; ***p<0.01

in a non-experimental setting, where the treatment is defined as a discontinuous function of a continuous, observed variable (the ‘running’ or ‘forcing’ variable). Like Thistlethwaite and Campbell (1960), who estimated the effect of receiving the National Merit Scholarship on future academic outcomes, early studies that rely on RD designs estimate the effects of certain thresholds of a running variable on educational outcomes (i.e., financial aid (Klaauw 2002) or class size (Angrist and Lavy 1999)). Following these early studies in education, the RDD has received attention in a broader range of the economic literature, including labor economics, political economy, health economics, and environmental economics. Compared to alternative quasi-experimental estimators like difference-in-difference and matching techniques, RDD is the estimator with the most significant internal validity (Lee and Lemieux 2010).

While RDD was applied initially in cross-sectional studies, an increasing number of studies, especially in environmental and energy economics, have adapted the framework to time series applications. In these studies, time is the running variable, and treatment begins at a particular threshold in time. A significant conceptual difference between regression discontinuity (RD) and regression discontinuity in time (RDiT) lies in the possible interpretation of the results. Since in RDiT, the running variable of time is not random eliminates the interpretation of local randomization. As noted by Jacob et al. (2012), although some researchers have focused on this interpretation of local randomization, in which the treatment status within a small neighborhood around the threshold can essentially be compared to a roll of the dice (Lee and Lemieux 2010), others have emphasized that RD is characterized by discontinuity at a threshold (Hahn, Todd, and Van der Klaauw 2001). Thus, to the extent that the RD framework is simply another quasi-experimental framework (one that uses discontinuity), RDiT is conceptually similar to RD.

In this paper, the date is the running variable, the election day is the treatment, and news publishers are the units that receive the treatment. A sharp regression design is used since the running variable (date) ultimately determines the treatment (election day). Thus, a news publisher's probability of receiving a treatment jumps from 0 to 1 at the cutoff. Specifically, the following equation is estimated:

$$\ln(\mathrm{CS}_t) = \beta_0 + \beta_1 T_t + f(W_t) + \epsilon_t$$

where

$$T_t = \begin{cases} 1, & \text{if date } \geq \text{election date} \\ 0, & \text{if date } < \text{election date} \end{cases}$$

The running variable W_t is the time difference between date i and the election date (in days), such that β_1 is the average treatment effect for observations with $W_t = 0$ (the election date). In other words, β_1 gives the average change of the similarity between news publisher content and press releases after the election day. Identification in the RD model comes from assuming that the underlying, potentially endogenous relationship between ϵ_t and the date is eliminated by the flexible function $f(.)$. In particular, the relationship between ϵ_t and the date must not change discontinuously on or near the election date.

Following Imbens and Lemieux (2008) I estimate a local linear regression model of the form:

$$\ln(\mathrm{CS}_t) = \beta_0 + \beta_1 T_t + \beta_2 W_t + \beta_3 W_t * T_t + \epsilon_t$$

In this specification (results are shown in RDiT Results), the function $f(W_t)$ is specified as $\beta_2 W_t + \beta_3 W_t * T_t$, where by $W_t * T_t$ is assumed that in addition to the intercept (captured by the treatment effect T_t), the slope also changes after the election day. The interaction term, together with W_t, should absorb any smooth relationship between the date and ϵ_t in the days surrounding the election day. Thus, if the RD assumption is valid (i.e., ϵ_t does not change discontinuously at the election day), the estimate of β_1, the coefficient of interest, will be unbiased even without further controls.

However, in section RDiT dummy results dummy variables for each party k ($D_{t,k-1}$) are included, to test the assumption that the effect of the election day on topic similarity differs for different parties. Here again, the interaction term $T_t * D_{t,k-1}$ allows for a slope change depending on the party. Thus β_5 gives the average treatment effect for each newspaper/party pair.

$$\ln(\mathrm{CS}_t) = \beta_0 + \beta_1 T_t + \beta_2 W_t + \beta_3 W_t * T_t + \beta_4 D_{t,k-1} + \beta_5 T_t * D_{t,k-1} + \epsilon_t$$

I specify a uniform kernel (Lee and Lemieux 2010) and use a bandwidth of 115 days on each side of the election day threshold. The election took place on September 24, 2017, so the sample includes dates between June 1, 2017, and January 17, 2018. Since the identification strategy only attempts to estimate β at $W_t = 0$ (the election day), no additional dates beyond the 115-day bandwidth enter the sample. Alternative specifications with varying bandwidths led to similar results.

RDiT Results

Table 8 shows the results of this estimation. The negative and significant values for β_1 indicate that - holding the time constant - the election day is associated with a decrease in topic similarity for DIE WELT, stern.de, ZEIT ONLINE, and Handelsblatt. Since I am interested in the treatment effect at the cutoff point (remember that $W_t = 0$ for the election day) and since

$$\frac{\Delta Y}{\Delta T} = \beta_1 + \beta_3 W,$$

β_1 can be interpreted as the change in topic similarity with respect to the election day. Similarly to the interpretation in OLS dummy results, the the % impact of T on Y can be estimated as $exp(\beta_1) - 1$. Figure 12 shows the transformed coefficients for all newspapers: The negative effect of the election day on the topic similarity is strongest for Handelsblatt (~21.5% decrease), followed by DIE WELT (~15.6% decrease), ZEIT ONLINE (~13.5% decrease) and stern.de (~11.1% decrease).

Table 8: Results from the RDiT model

	Dependent variable:						
	Cosine similarity of topic distribution						
	DIE WELT	stern.de	ZEIT ONLINE	Handelsblatt	FOCUS Online	Bild.de	SPIEGEL ONLINE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
T	-0.169^{***}	-0.118^{**}	-0.145^{**}	-0.242^{***}	-0.058	-0.032	0.035
	(0.045)	(0.057)	(0.065)	(0.060)	(0.048)	(0.066)	(0.055)
W	-0.001^{*}	-0.0005	-0.002^{***}	-0.0003	-0.001	-0.001	-0.002^{***}
	(0.0004)	(0.001)	(0.001)	(0.001)	(0.0005)	(0.001)	(0.001)
TTRUE:W	0.003^{***}	0.003^{***}	0.002^{*}	0.005^{***}	0.002^{**}	0.003^{***}	0.003^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	-1.972^{***}	-2.181^{***}	-1.927^{***}	-1.812^{***}	-2.091^{***}	-2.080^{***}	-2.160^{***}
	(0.029)	(0.036)	(0.045)	(0.043)	(0.033)	(0.046)	(0.038)
Observations	1,212	1,218	1,244	1,046	1,268	1,161	1,264
R^2	0.031	0.011	0.059	0.035	0.005	0.013	0.009
Adjusted R^2	0.028	0.009	0.056	0.032	0.003	0.011	0.007
Residual Std. Error	0.377 (df = 1208)	0.471 (df = 1214)	0.586 (df = 1240)	0.491 (df = 1042)	0.427 (df = 1264)	0.579 (df = 1157)	0.495 (df = 1260)
F Statistic	12.805^{***} (df = 3; 1208)	4.655^{***} (df = 3; 1214)	25.810^{***} (df = 3; 1240)	12.532^{***} (df = 3; 1042)	2.134^{*} (df = 3; 1264)	5.154^{***} (df = 3; 1157)	3.820^{***} (df = 3; 1260)
Note:							*p<0.1; **p<0.05; ***p<0.01

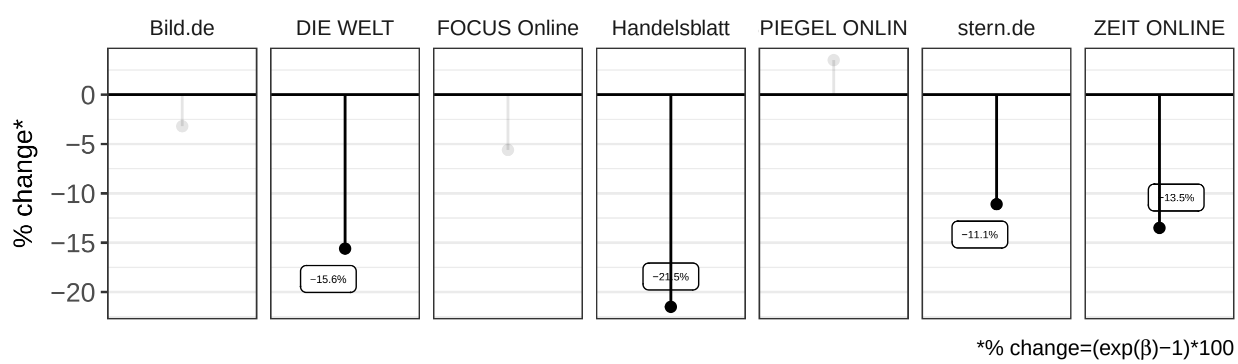


Figure 12: Treatment effect of RDiT regression

RDiT dummy results

As mentioned above, I assume that the effect of the election day on the topic similarity is different for different parties. Figure 13 visually captures the treatment effect for two sample news publishers Handelsblatt and Bild.de. It reveals a treatment effect around the cutoff point for Handelsblatt and CDU, FDP, and B90/GRÜNE: For all pairs, the topic similarity decreases right after the election day. The same is true for Bild.de and AfD (see Figure 15 for all news publishers). Thus, a positive effect can only be found for Bild.de and B90/GRÜNE and Bild.de and CDU. The figure also illustrates a slope change after the election day for nearly all newspaper/party pairs.

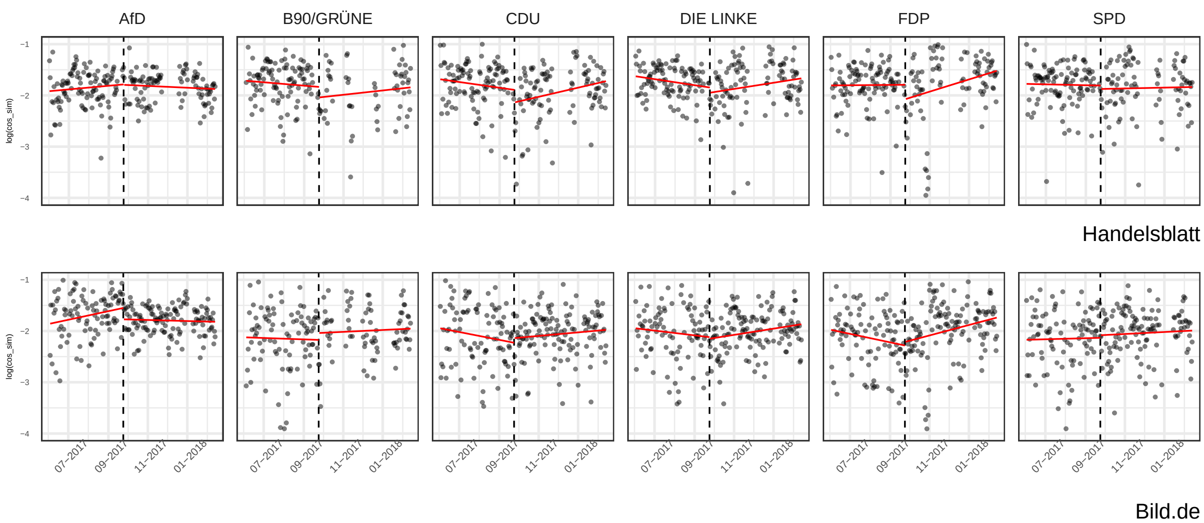


Figure 13: Log of mean cosine similarity between newspaper/press articles pairs - with cutoff value

Table 9 outputs the results for all newspaper models. The coefficients for the treatment variables (e.g., "TTRUE:B90/GRÜNE") show the effect of the election day's effect on the topic similarity depending on the party for a given W. This effect can be illustrated using Handelsblatt and B90/GRÜNE as an example and comparing the model equation for $D_{B90/GR\ddot{U}NE} = 1$ and $D_{B90/GR\ddot{U}NE} = 0$ for $W = 0$. For $D_{B90/GR\ddot{U}NE} = 1$ the equation is

$$\ln(\text{CS}) = -1.896 + (-0.091)T + (-0.260)T,$$

whereas for $D_{B90/GR\ddot{U}NE} = 0$ it is

$$\ln(\text{CS}) = -1.896 + (-0.091)T.$$

In other words, when $D_{B90/GR\ddot{U}NE}$ switches from 0 to 1, the treatment effect decreases by 0.260 compared to the base dummy group AfD, for which the treatment effect is -0.091. Again, since I estimate a log-linear regression model, the coefficient should be transformed using $\exp(-0.260) - 1 = -0.229$. Therefore, the topic similarity between Handelsblatt and

B90/GRÜNE decreases right after the election day by 22.9% compared to AfD (the base dummy group).

Table 9: Results from the regression discontinuity model

	Dependent variable:						
	Cosine similarity of topic distribution						
	DIE WELT	stern.de	ZEIT ONLINE	Handelsblatt	FOCUS Online	Bild.de	SPIEGEL ONLINE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
T	−0.167***	−0.048	−0.038	−0.091	−0.072	−0.187*	0.076
	(0.063)	(0.081)	(0.096)	(0.090)	(0.068)	(0.097)	(0.081)
W	−0.001*	−0.0005	−0.002***	−0.0003	−0.001	−0.001	−0.002***
	(0.0004)	(0.001)	(0.001)	(0.001)	(0.0005)	(0.001)	(0.001)
B90/GRÜNE	−0.267***	−0.215***	−0.180**	0.105	−0.337***	−0.445***	−0.186***
	(0.048)	(0.062)	(0.078)	(0.067)	(0.054)	(0.081)	(0.064)
CDU	−0.259***	−0.115*	−0.232***	0.098	−0.288***	−0.450***	−0.170***
	(0.048)	(0.061)	(0.078)	(0.067)	(0.054)	(0.081)	(0.064)
DIE LINKE	−0.251***	−0.109*	−0.160**	0.134**	−0.270***	−0.342***	−0.156**
	(0.048)	(0.061)	(0.078)	(0.067)	(0.054)	(0.081)	(0.064)
FDP	−0.291***	−0.195***	−0.201***	0.069	−0.355***	−0.441***	−0.292***
	(0.048)	(0.061)	(0.078)	(0.067)	(0.054)	(0.081)	(0.064)
SPD	−0.278***	−0.143**	−0.201***	0.098	−0.339***	−0.479***	−0.266***
	(0.048)	(0.061)	(0.078)	(0.067)	(0.054)	(0.081)	(0.064)
TTRUE:W	0.003***	0.003***	0.002*	0.004***	0.002**	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
TTRUE:B90/GRÜNE	0.058	−0.137	−0.249**	−0.260**	0.055	0.223*	−0.032
	(0.079)	(0.101)	(0.124)	(0.120)	(0.087)	(0.124)	(0.103)
TTRUE:CDU	−0.080	−0.222**	−0.161	−0.272***	−0.073	0.149	−0.165*
	(0.070)	(0.090)	(0.111)	(0.104)	(0.078)	(0.112)	(0.092)
TTRUE:DIE LINKE	−0.062	−0.089	−0.122	−0.162	−0.074	0.092	−0.134
	(0.070)	(0.090)	(0.111)	(0.104)	(0.078)	(0.112)	(0.092)
TTRUE:FDP	0.066	0.078	−0.083	−0.061	0.104	0.219*	0.107
	(0.071)	(0.090)	(0.111)	(0.104)	(0.078)	(0.112)	(0.093)
TTRUE:SPD	0.020	−0.093	−0.087	−0.173	0.062	0.244**	−0.010
	(0.071)	(0.091)	(0.112)	(0.105)	(0.079)	(0.113)	(0.093)
Constant	−1.747***	−2.051***	−1.765***	−1.896***	−1.826***	−1.721***	−1.982***
	(0.042)	(0.053)	(0.067)	(0.061)	(0.047)	(0.069)	(0.056)
Observations	1,212	1,218	1,244	1,046	1,268	1,161	1,264
R^2	0.111	0.052	0.091	0.047	0.089	0.069	0.053
Adjusted R^2	0.101	0.042	0.082	0.035	0.080	0.059	0.043
Residual Std. Error	0.362 (df = 1198)	0.463 (df = 1204)	0.578 (df = 1230)	0.490 (df = 1032)	0.410 (df = 1254)	0.564 (df = 1147)	0.486 (df = 1250)
F Statistic	11.491*** (df = 13; 1198)	5.087*** (df = 13; 1204)	9.506*** (df = 13; 1230)	3.915*** (df = 13; 1032)	9.423*** (df = 13; 1254)	6.584*** (df = 13; 1147)	5.364*** (df = 13; 1250)
Note:							*p<0.1; **p<0.05; ***p<0.01

Figure 14 displays the transformed coefficients of the interaction terms. Note that the coefficient of the treatment effect (without interaction) shows the treatment effect for AfD since it is the base dummy group. While in the previous model without party dummies, the treatment effect for Bild.de was not significant, the present model shows a significant negative effect for the topic similarity for Bild.de and AfD (−17%), as well as a significant positive effect between Bild.de and B90/GRÜNE (25%), SPD (27.7%) and FDP (24.4%). In the case of DIE WELT, the only significant effect is the one regarding AfD: The topic similarity decreases by about 15.4% shortly after election day, which roughly corresponds to the total treatment effect found in the previous model. Also, the results show a decrease in the topic similarity between CDU and the online news of Handelsblatt (23.8%), SPIEGEL ONLINE (15.2%), and stern.de (19.9%. In the case of Handelsblatt, a similar negative effect exists for B90/GRÜNE (22.9%). The same is true for ZEIT ONLINE, where the topic similarity decreases for B90/GRÜNE right after the election day by 22%. No effect of the election day can be detected in the case of FOCUS ONLINE on neither of the model specifications.

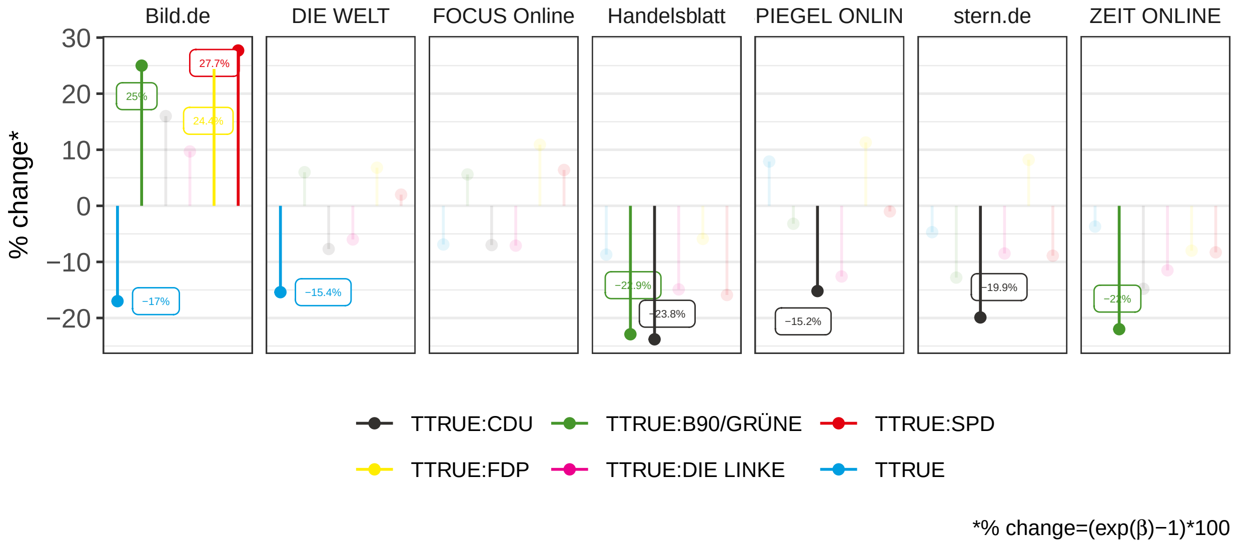


Figure 14: Coefficients of RDiT dummy regression

VI Discussion and conclusion

In the run-up to the 2017 federal election, German media was accused of indirectly influencing the election through its political coverage. On the one hand, it was accused of providing a stage for the AfD through its choice of topics, which led to a rise in the party's popularity. But, on the other hand, the AfD accused the same media of devaluing the party through negative reporting.

This paper investigates whether political reporting of German online newspapers was similar for the major political parties during the election campaign for the Bundestag 2017. Results show that the news articles of all newspapers (except for Handelsblatt) are significantly more similar to press releases of the AfD than any other party.

Although no statement can be made about the tonality with which AfD-related issues are discussed, it can be assumed that the mere disproportionate mention of these topics in the media has brought the party more into the focus of voters. The assumption that the RDiT results can partially confirm coverage changes as Election Day approaches: Although the topic probability decreases for almost all news providers, except for FOCUS ONLINE, there are considerable differences with regard to the parties.

Annex

Table 10: 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 11: 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, höcke
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, frauke, 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, erdogan, türkischen, deutschland, bundesregierung, türkische, deutsche
32	frauen, deutschland, kinder, studie, eltern, muslime, 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, leyen, 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

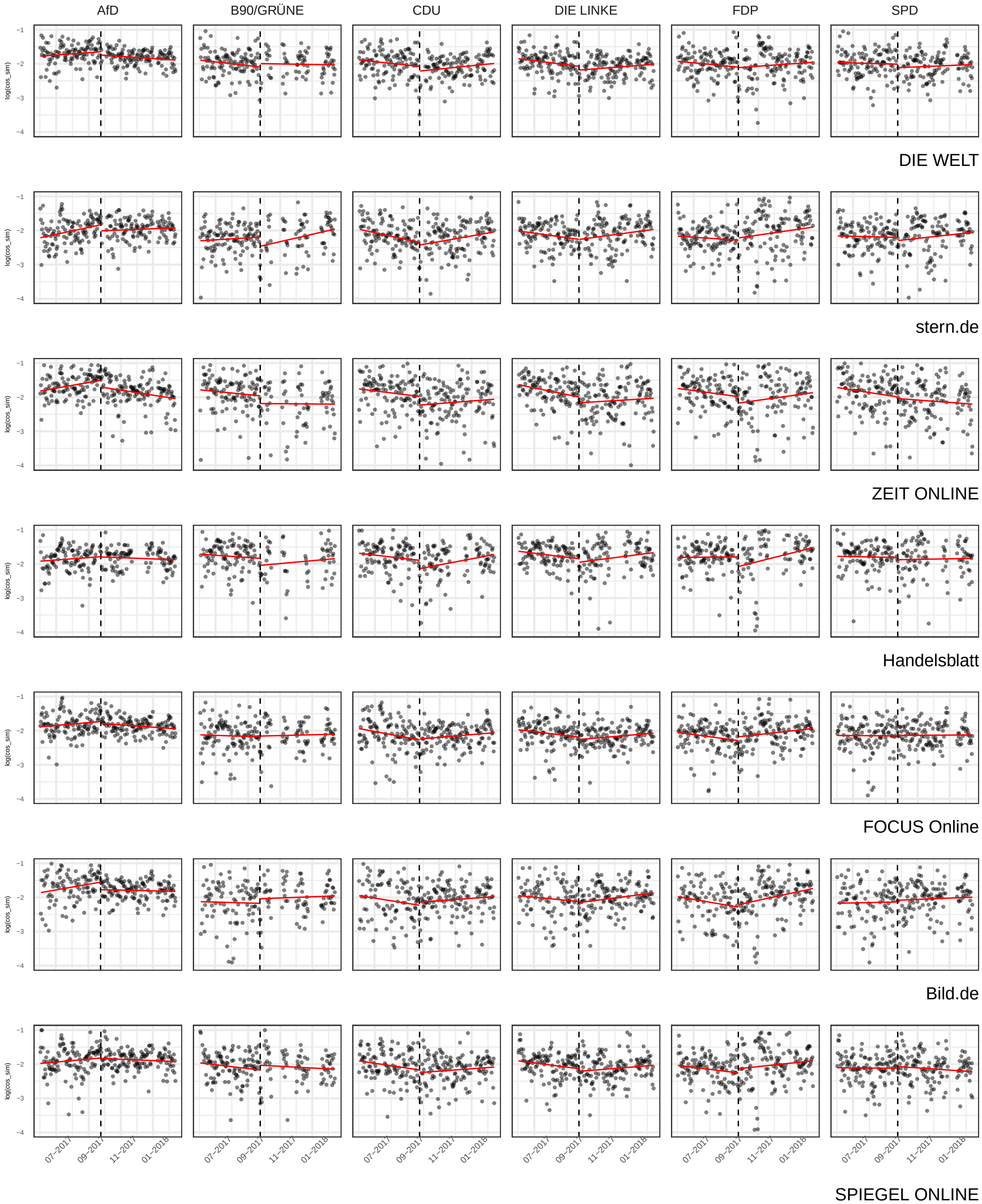


Figure 15: Log of daily mean cosine similarity between newspaper/press articles pairs - with cutoff value

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