1 Introduction

In Germany, the debate about the role of public media and their mission in a rapidly changing media world is a recurring theme. By shifting media content to the Internet, the dual system, which has been shaping the German television and radio landscape since the introduction of private broadcasting in the early 1980s, is facing a radical change. Since 2000, public broadcasting has expanded its range of services, particularly in the digital media sector. If the right to produce digital media content were to be withdrawn from the public media outlets, they would not only be deprived of the possibility of improved information provision. They also threatened to lose their competitiveness with commercial media. On the other hand, there is the concern of commercial providers who are registering an ever-increasing number of digital services financed by fees. They complain about a bias in competition caused by public media offering online text-content because of their fee financing. The advertising-financed business model of the media houses is based on the premise that users visit their websites in order to achieve high advertising revenues.

One fundamental question in this debate is whether the offer of public news on the internet is justified. They should only occur where there are clear deficits in private sector supply. A frequently cited argument is that only the public media make it possible to provide information that is free of self-interest. Due to their public mandate and financing, they can afford what private providers cannot or only to a limited extent because of their economic dependency: a journalistic and editorial self-observation of society in the public interest. Due to their constitutional determination, they are obliged to the diversity and representation of the political and social spectrum of opinion in its entire breadth, including minority positions.

On the basis of these justifications, this paper examines whether public media offer different content than private providers. In order to examine this, the online news content of public media is compared with the supply of private news providers.

We use a data set of German online news articles about domestic politics dated from 01.06.2017 to 31.12.2017[1] from six German content providers.

The research strategy is as follows:

1. **Discovering Topics** Discover latent topics in the corpus using structural topic modeling (STM)(M. E. Roberts, B. M. Stewart, and E. M. Airoldi, 2016) An extension of latent dirichlet allocation (LDA) (Blei,

[1] German federal elections took place on 24th of September 2017.

Ng, and Jordan, 2003)). The STM approach models (a) topics as multinomial distributions of words and (b) documents as multinomial distributions of topics, allowing to incorporate external variables that effect both (a) topical content and (b) topical prevalence. To explore the results, we label each topic by looking at most frequent words and most representative articles across all news providers. (Section 3)

2. **Measuring Similarity of news content** Different approaches to examine the similarities / differences of content between the news provider:

   (a) **Differences in topic prevalence:** As we allow prevalence of topics to evolve over time (by month) and vary across newswire services, we can use the posterior topic-probability of document d, to estimate the conditional expectation of topic prevalence θ_d for given document characteristics (lm on compositional data) (M. E. Roberts, B. M. Stewart, and E. M. Airoldi, 2016).

   $$\theta_d = \alpha + \beta_1 x_{site} + \beta_2 x_{month} + \epsilon$$

   (b) **Topic correlation** How are topics linked and framed differently across news wires? Find all edges between topics where they exhibit a positive correlation above 0.1 (M. E. Roberts, B. M. Stewart, and E. M. Airoldi, 2016).

   (c) **Differences in word-topic distributions** From the STM we get a KxV matrix (where K = number of topics and V = vocabulary) of the whole corpus that contains the probability of seeing each word of the vocabulary V within topic k conditional on the news provider. That is, for each news provider we get a respective KxV matrix. We then use each row (corresponding to each topic) to calculate the similarity of the word-topic distribution between the news provider using the square root of the Jensen-Shannon (JS) Divergence.

   Previous topic modeling research try to measure the similarity between topics, comparing the word-topic-distribution between the topics (most of the research uses LDA without metadata, so the word-topic-distribution is the same within the whole corpus). cosine similarity (He et al., 2009), (Ramage et al., 2009), Kullback-Leibler (KL) (Newman et al., 2009), (Wang et al., 2009) and the average Log Odds Ratio (Chaney and Blei, 2012) are frequently used metrics to compare word probability distributions. Kim and Oh (2011) compare six popular similarity metrics in terms of log

likelihood of data, concluding that Jensen-Shannon Divergence (the symmetric variation of KL divergence) is best in terms of performance and generality.

2 The online news market

The market for media content in Germany is characterized by the coexistence of public and private broadcasters. By shifting media content to the Internet, the dual system, which has been shaping the German television and radio landscape since the introduction of private broadcasting in the early 1980s, is facing a radical change. Since 2000, public broadcasting has expanded its range of services, particularly in the digital media sector. In 2017, 22 own websites and 100 apps were operated by public broadcasters on which they offer their content. As a result, public broadcasting no longer only competes with private television and radio stations, but also enters the market for online news. In the following, we will briefly discuss the characteristics of the market for online news.

Private media outlets naturally appear as two-sided platforms, that allow interaction between two categories of consumers: audiences and advertisers. As the demand on both consumer-sides are linked via indirect network externalities, the market in which media outlets operate are referred to as two-sided or multi-sided markets. The theoretical literature on two-sided markets originates from the analysis of credit card markets (Rochet and Tirole, 2003) and was later transferred to the concept of other industries, such as dating agencies, real estate agents, and internet "business-to-business" websites (Caillaud and Jullien, 2003). The basic concept of two-sided markets was already discussed decades ago in several economic studies, especially on media markets (Corden, 1952), (Gustafsson, 1978), (Blair and Romano, 1993). However, comprehensive analyses have only been carried out in the last ten years, starting with the works of Rochet and Tirole (2003), Evans (2003) and Armstrong (2006).

Advertising-supported media such as online newspapers are typical examples of two-sided markets where the newspaper can be conceived as platforms that allow interaction between audiences ("eyeballs") and advertisers. The newspaper creates (or buys) content to attract viewers which in turn attract advertisers who pay for readers' attention.Evans and Schmalensee, 2005 The size and characteristics of the audience has a positive effect on the advertisers' willingness to pay, as advertisements are typically sold based on cost per viewer, often expressed in terms of the cost of reaching a thousand viewers (CPM). Advertising can also have an effect on the recipients, which can

be both negative and positive, depending on the quality of the advertising. Depending on the strength of the indirect network effects, private publisher maximize their revenue by balancing the demand from advertisers and subscribers using different business models (Evans, 2008). Many traditional newspapers follow the subscription/advertising model, where the publisher charges both market sides: The audience pays a fee to obtain access to the content, and advertisers pay to obtain access to the viewers. Many online news agencies provide part of their editorial content for free and hide another, more exclusive part behind a paywall. However, since the Internet has considerably simplified the possibilities for obtaining information and thus reduced the marginal utility of content, such a business model can only be efficient if the content is very exclusive. As a result, many publishers rely on a free-media model, in which the publishers do not charge viewers for access to the media at all, in order to attract as many eyeballs as possible to their platform, and thus exploit the indirect network effects on the advertising site. In fact, most advertising-financed online magazines earn their gross margin from advertising.Evans and Schmalensee, 2005 In order to maximize their profits, these companies have an interest in attracting as many readers as possible. In addition to the quantity of the audience, the demographic characteristics of recipients also have an influence on the willingness to pay on the advertiser site. Online advertising makes it possible to target ads to particular consumers in real time.

The two-sided market structure of the private news markets results in news platforms striving to choose their content in such a way that its reach is as large as possible in order to maximize profits from advertising revenues. (Steiner, 1952) concluded, that profit-maximizing media owners may choose to offer the same content, i.e. content aligned with the tastes of the majority. (Gabszewicz, Laussel, and Sonnac, 2001) study the problem of diversity of the political content of newspapers. They find that the maximum differentiation only prevails if the readers sufficiently value the political differentiation between the newspapers the advertising market is small enough. On the other hand, advertising may also have a positive impact on the media, as it enables publishers to report independently of political parties. Ellman and Germano (2009) found that advertising increases the intensity of competition for readers and therefore raises accuracy of media coverage.

Given the crucial role of the media in shaping opinion and promoting democracy, pluralism of opinion and accuracy of information is a major concern of public authorities. Public broadcasting in Germany originated in the post-war period and has always had the task of providing the entire population with independent media. This media offer is intended to guarantee diversity of opinion within the media landscape and to be economically and

politically independent. The former is given by the fact that the public media are financed by compulsory fees. To take into account the distinct nature of digital media, the Interstate Broadcasting Agreement (Rundfunkstaatsvertrag) also regulates the scope for action of online services offered by public service broadcasting since 2007. Accordingly, public media are not allowed to distribute purchased content and must - depending on the category of content - set a time limit on its accessibility. In addition, there is a strict advertising ban and prohibition of regional reporting.

However, given today's media landscape, the role of public media provider and its mandate is in discussion. The basic justification for a public media offer can be roughly divided into two categories: On the one hand, possible market failure and on the other hand, ensuring diversity. The former involves the pursuit of non-economic (e. g. democratic, social and cultural) objectives, as well as the provision of information that would not be made available by the market due to a lack of willingness to pay. Ensuring the diversity of media content is intended to counteract possible media bias.

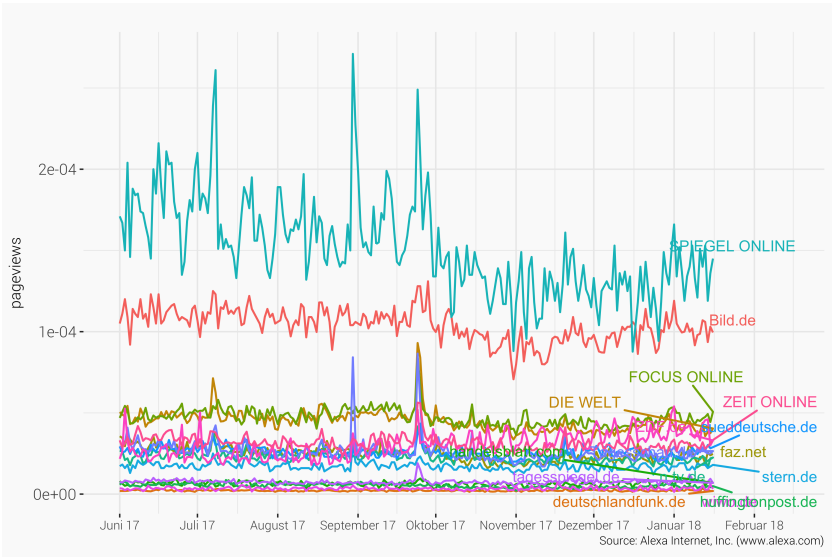
On the basis of these justifications, this paper examines whether imperfections in the market of online news exist. In other words, whether socially desired content that meets the (social) needs of society and is therefore politically desirable is not provided by the market. In order to examine this, the online news content of public media is compared with the supply of private news providers. In the event that there is no market failure in terms of information provision (the contents do not differ), the existence of public media could still be justified by the fact that socially relevant contents of private providers are systematically distorted and the existence of public offerings ensures the diversity of information and opinions transmitted.

2.1 Competitor analysis

Figure 1a shows the largest providers of online news in terms of daily pageviews.[2] It is striking that SPIEGEL ONLINE has the greatest reach over the entire course of time followed by Bild.de.

[2]The figure shows the estimated percentage of daily pageviews on the internet that occurred on a specific website.

Figure 1



(a) Percentage of daily pageviews

Users can access a website either directly or through an intermediary, such as search engines or social media. As the figure 2 illustrates[3], direct access[4] to a website is the main source of traffic for most news providers. In the case of Bild.de, the percentage is 85%. Also n-tv.de (79%), spiegel.de (76%) and tagesschau.de (75%) get most of their traffic via the direct route. Other providers are more reliant on intermediaries, mainly search engines. Focus.de, Deutschlandfunk.de, Handelsblatt.com, for example, obtain between 40% and 45% of its traffic via search engines. Thus, an important question is, which organic search keywords send traffic to a website. Figure 3 displays the percentage of organic search referrals to a specific website that come from this keyword.[5] E.g., 0.78% of all organic search referrals to handelsblatt.com come from the keyword "handelsblatt". It is not surprising that the provider's name is the keyword that generates the majority of traffic for most of the news pages. However, different topics as well as names

[3]The figure shows the percentage of total traffic by a source for the time period 18.12.2017-18.01.2017

[4]Direct traffic includes: Direct navigation (Someone types the website URL into a browser); Bookmarks (Clicks on a bookmark/favorite link in a browser); Email (Clicks on links in desktop email clients)

[5]Percentage of organic search referrals in major search engines over the time span Jun-Dec 2017.

of other providers are hidden among the top 10 keywords.

Figure 2: Traffic Sources

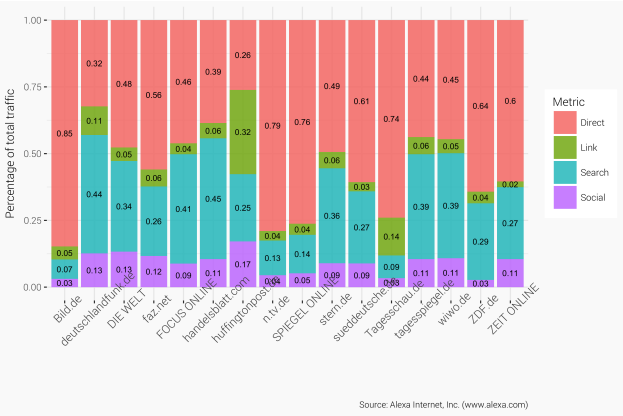
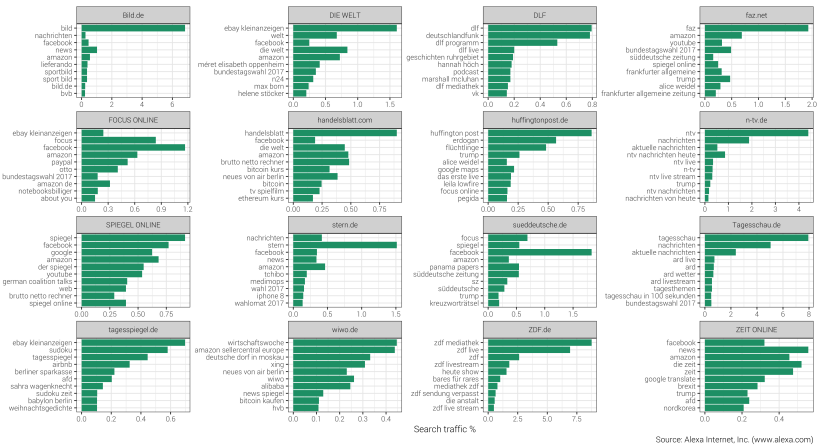


Figure 3: Search traffic %



Assuming that each search query is in itself a market where providers compete for traffic, the share of search queries for a keyword that has led visitors to a news page is the market share of that provider. In this context, figures 4 and 5 show the market share of providers for different keywords.[6]

[6]The figures show the percentage of searches for a keyword that sent traffic to a website in major search engines over the time span Jun-Dec 2017.

Nearly 15% of all search queries for the keyword "Bundestagswahl 2017" (federal elections 2017) were forwarded to DIE WELT. FOCUS ONLINE, faz.net and SPIEGEL ONLINE obtained a market share of 7% - 8%. For the keyword "Groko" (grand coalition between CDU/CSU and SPD), SPIEGEL ONLINE was able to gain the largest market share (17%) in the past six months, followed by DIE WELT (%10), FOCUS ONLINE (8%) and Bild.de (7.5%). Figure 5 shows the market share of news pages for the keyword search for a specific party.

Contrary to figure 4 , the x-axes in figure 5 are scaled equally to show not only the market share of news sites for a specific party-keyword, but also for which party this provider has the largest market share. For example, we can see that the market share of sueddeutsche.de is largest for the keyword "Die Grünen". However, the biggest market share among the listed news providers for this keyword has Zeit.de. The largest market share for the keyword "AfD" can be found at DIE WELT, followed by SPIEGEL ONLINE. The proportion of public news providers is comparatively low for all keywords.

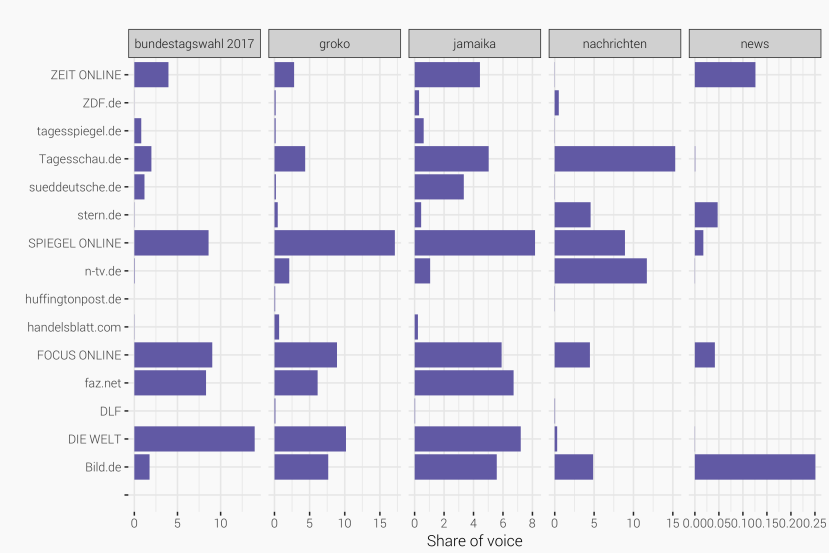


Figure 4: Keyword market share for policy topics / general

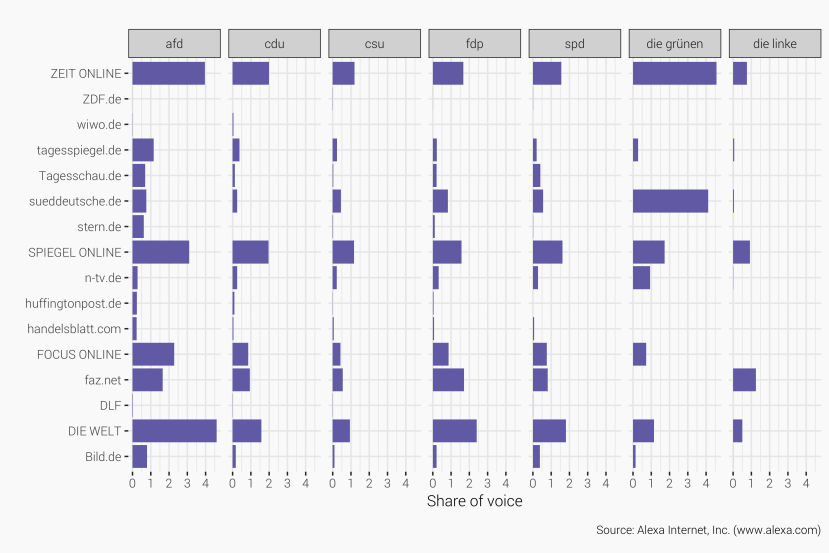


Figure 5: Keyword market share for party-keywords

2.2 Dataset

We conduct our estimation on a sample of 9393 online news articles from six news provider about domestic politics[7], of which only Tagesschau.de belongs to the group of public provider. The reason for this is that the content of Tagesschau.de is most similar to that of the private providers. ZDF.de offers predominantly video content and DLF website mainly offers audio content in the form of interviews. The articles are dated from 01.06.2017 to 31.12.2017.[8] We first extract all online articles using the the Webhose.io API.[9] We then filtered all articles from the section "domestic policy" by checking the URL structure.

Figure 6a shows the distribution of the number of articles from the respective news sources by date. There is a high peak around the federal elections on September, 24th.

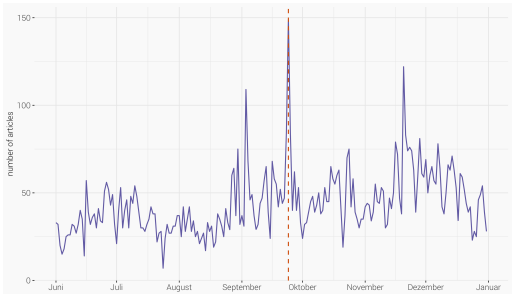
Separate by ownership and explain why article distribution repre-

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

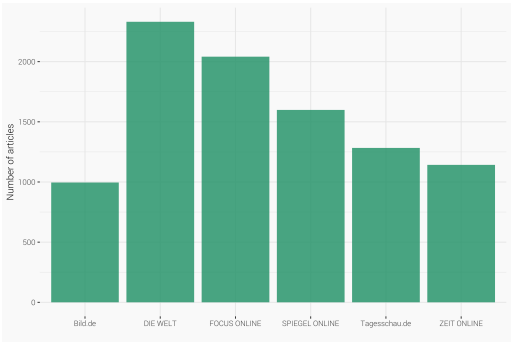
[8]German federal elections took place on 24th of September 2017.

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

Figure 6: Article distribution...



(a) ...by date



(b) ... by news source

To use text as data and reduce the dimensionality, a common strategy is to pre-process the text by imposing some preliminary restrictions (stop-word removal, tokenization) based on the nature of the data (twitter text, newspaper articles, speeches, etc.) to reduce the number of language elements to consider (Gentzkow, Kelly, and Taddy, 2017). An overview of how these steps were applied to our data set can be found in the next section.

After pre-processing, each document d is a finite list of terms. Each unique term in the corpus is indexed by some $v \in \{1, ..., V\}$ where V is the number of unique terms. For each document $d \in \{1, ..., D\}$ we compute the number of occurrences of term v in document d to obtain the count $x_{d,v}$. The D x V matrix $\boldsymbol{X}$ of all such counts is called the document-term matrix. This representation is often referred to as the bag of words model, since the order in which words are used within a document is completely disregarded.

A central task in text mining is to extract low-dimensional information from documents that are high-dimensional by nature (Bholat et al., 2015). This is related to the task of reducing the number of unique language elements in order to reduce the dimensionality of data (to avoid unnecessary computational complexity and overfitting) while at the same time keeping those words that reflect the content of a document. Any useful representation of text will throw away some information, the trick is to include the relevant information for our needs, and exclude the extraneous information.

Intuitively the term frequency (tf) of a word is a measure of how important that word may be. There are words in a document, however, that occur many times but may not be important like articles, conjunctions, and so on. These terms, often called "stop words", are important to the grammatical structure of a text, but typically don't add any additional meaning and can

therefore be neglected. We use a pre-defined stop word list from the Snowball stemmer project[10] together with a customized list of stop-words that are redundant superfluous or distorting. We also remove punctuation character (e.g. ., „ !, ?, etc.) and all numbers from our corpus.

2.3 Similar Research

M.Paul (Cross-Collection Topic Models: Automatically Comparing and Contrasting Text): compares editorial differences between media sources, using cross-collection latent Dirichlet allocation (ccLDA), an LDA-based approach that incorporates differences in document metadata. They use a dataset of 623 news articles from August 2008 from two American media outlets - msnbc.com and foxnews.com - to analyse how they discuss topics differently. Comparing the top words of the word-topic distribution, they find some content differences between the two.

3 The structural topic model

We use the structural topic model (STM) developed by M. E. Roberts, B. M. Stewart, and E. M. Airoldi (2016) that allows us to incorporate document specific covariates (e.g. the author or date of a document). STM is a recent 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.[11] Topic models formalize the idea that documents are formed by hidden variables (topics) that generate correlations among observed terms. Since its introduction into text analysis, LDA has become hugely popular and especially useful in political science.[12] Wiedmann (2016) use topic model methods in on large amounts of news articles from two german newspapers published between 1959 and 2011, to reveal how democratic demarcation was performed in Germany over the past six decades.

STM has been applied to multiple academic fields: M. E. Roberts, B. M. Stewart, Tingley, et al. (2014) uses STM to analyse open-ended responses

[10] http://svn.tartarus.org/snowball/trunk/website/algorithms/*/stop.txt

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

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

from surveys and experiments, Farrell (2016) applies the model to scientific texts on climate change, revealing links between corporate funding and the framing of scientific studies and Mishler et al. (2015) shows that "STM can be used to detect significant events such as the downing of Malaysia Air Flight 17" when applied to twitter data. Another study shows how STM can be used to explore the main international development topics of countries' annual statements in the UN General Debate and examine the country-specific drivers of international development rhetoric (Baturo, Dasandi, and Mikhaylov, 2017). Mueller and Rauh (2016) uses newspaper text to predict armed conflicts in different regions. They use the estimated topic shares in linear fixed effects regression to forecast conflict out-of-sample. In order to demonstrate multi-modality of topic-models[13] can be mitigated, (M. Roberts, B. Stewart, and Tingley, 2016a) use STM to examine the role of partisanship in topical coverage using a corpus of 13,246 posts that were written for 6 political blogs during the course of the 2008 U.S. presidential election. With the aim of revealing the effect of partisan membership on topic prevalence, each blog is assigned to be either liberal or conservative. To explore the differences between the two, they look at the expected proportion of topic and examine the posts most associated with a respective topic. This approach is similar to M. E. Roberts, B. M. Stewart, and E. M. Airoldi (2016). They also use different measures of distance between the topic-word distributions of the same topic within different models. In section 4.3, we apply a similar approach to measure similarity between the same topic for different covariate levels.

3.1 Generative Process of STM

As mentioned above, the STM allows to incorporate observed document metadata which is able to affect either topical prevalence and topical content. The following description of the generative model - the process of filling a word-position in a document - of the STM is based on M. Roberts, B. Stewart, Tingley, and E. Airoldi (2013) and M. Roberts, B. Stewart, and Tingley (2016b). For each document d and a given number of topics K, a document-specific topic-prevalence vector $d(\boldsymbol{\theta}_d)$ is drawn from a logistic-normal distribution, where the parameters are a function of the covariate values:

$$\boldsymbol{\theta}_d | \boldsymbol{x}_{d\gamma}, \boldsymbol{\Sigma} \sim \text{LogisticNormal}(\mu = \boldsymbol{x}_{d\gamma}\boldsymbol{\Sigma})$$

[13]That is, the solution of topic-models can be sensitive to the starting values as the function to be optimized has multiple modes.

$\boldsymbol{x}_d\gamma$ lists the values of all metadata covariates for document d, where γ relates these covariate values to the topic-prevalence. The structure of $\boldsymbol{\Sigma}$ implies the possibility of correlations across documents in the topic-prevalence vector.

According to θ, a specific topic z_{dn} is assigned for the n^{th} word-position in the document through the process

$$z_{dn}|\boldsymbol{\theta}_d \sim \text{Multinomial}(\boldsymbol{\theta}_d).$$

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

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

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

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

The STM maximizes the posterior likelihood that the observed data were generated by the above data-generating process using an iterative approximation-based variational expectation-maximization algorithm[14] available in R's stm package (M. Roberts, B. Stewart, and Tingley, 2016b). The process gives us two posterior distribution parameter: (1) β is a K-by-V matrix (where K = number of topics and V = vocabulary), where the entry β_{kv} can be interpreted as the probability of observing the v-th word in topic k. As we let covariate levels (the news provider) effect the word-distribution of a topic,

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

we will get as many β matrices as news provider. (2) θ is a D-by-V matrix of the document-topic distributions, where the entry θ_{dk} can be interpreted as the proportion of words in document d which arise from topic k, or rather as the probability that document d deals about topic k. We will use these probability distributions to compare the content of public and private news provider in Section 4.

3.2 Model and parameter selection

Inference of mixed-membership models, such as the one applied in this paper, has been a thread of research in applied statistics in the past few years (Blei, Ng, and Jordan, 2003) (Erosheva, Fienberg, and Lafferty, 2004) (Braun and McAuliffe, 2010). Topic models are usually imprecise as the function we are optimizing has multiple modes, such that the model results can be sensitive to the starting values. Since an ex ante valuation of a model is hardly possible, we compute a variety of different models and compare their posterior probability. This enables us to check how substantively different results are for different model solution (M. Roberts, B. Stewart, and Tingley, 2016a). We 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). We apply these manual audits together with numeric optimization based on the topic coherence measure suggested by Mimno et al. (2011).

This process revealed that a model with 40 topics best reflects the structure in the corpus. Furthermore, we use the ownership of the news provider of each article (public or private) and the month it was published as covariates in the topic prevalence. In other words, the probability distribution of topics depends on the business-model of a media house as well as on the month the article was published. We also include ownership as a covariate affecting topical content to estimate how topics are discussed in different ways by different news agencies. To address problems due to non-convexity, we rely on the spectral initialization approach advocated by M. Roberts, B. Stewart, and Tingley (2016a).

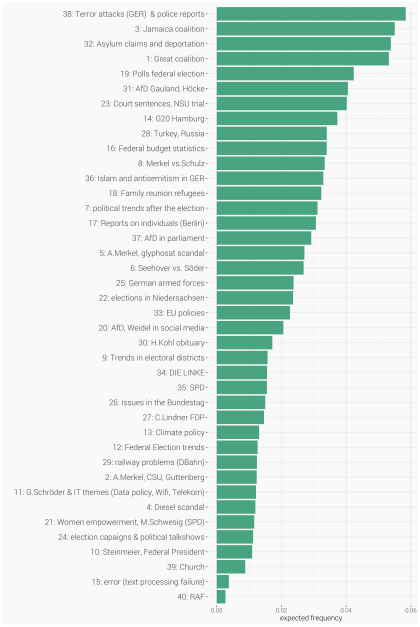
4 Empirical Evaluation

In this section we summarize the results of the STM and apply different measures to analyze the content differences between public and private ownership.

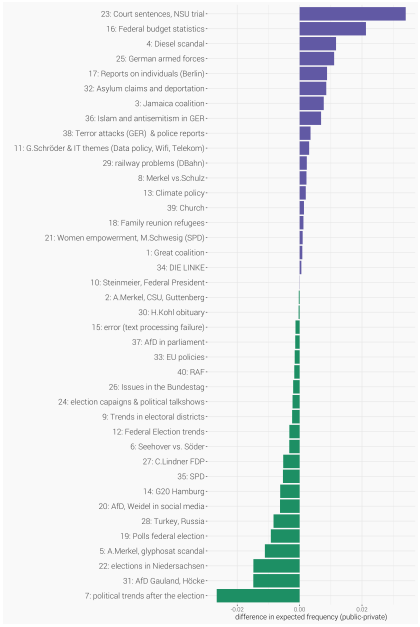
Figure 7a displays the topics ordered by their expected frequency across

the corpus. To assign a label to each topic, we looked at the most frequent words in that topic and the most representative articles (M. E. Roberts, B. M. Stewart, and E. M. Airoldi, 2016). Figure 7b plots the expected proportion of topic use in public media minus the expected proportion of topic use in private media. Thus topics more associated with public media appear to the right of zero.

Figure 7: Expected topic proportion



(a) Entire corpus



(b) Differences

We use various approaches to investigate the differences between news

provider content: (1) First, we use the document-topic probability θ, to estimate the conditional expectation of topic prevalence for given document characteristics. (2) Next, we find all edges between topics where they exhibit a positive correlation of θ above 0.1 to examine how topics are correlated differently for different news wires, indicating how topics are connected and framed differently in each newswire. Approaches (1) and (2) have been used in (M. E. Roberts, B. M. Stewart, and E. M. Airoldi, 2016) However, we extend the analysis by (3) calculaing the similarity of the word-topic distribution β between the news provider using different distance metrices, to identify which topics are discussed similar and differently.

(M. Roberts, B. Stewart, and Tingley, 2016a): Poliblog corpus to examine the role of partisanship in topical coverage.

Noch 1,2,3 studien angeben ,die das gemacht haben.

4.1 Differences in topic prevalence

Since we included news source as a covariate in estimating topical prevalence part within the model, we can estimate the frequency a topic is discussed within a news corpus (M. E. Roberts, B. M. Stewart, and E. M. Airoldi, 2016). We estimate the conditional expectation of topic prevalence for given document characteristics. More specifically, we estimate a linear model, where the documents are observations, the dependent variable is the posterior probability of a topic and the covariates are the metadata of documents (see equation 1). The stm-package provides a function that uses the method of composition to incorporates uncertainty in the dependent variable, drawing a set of topic proportions from the variational posterior repeated times and compute the coefficients as the average over all results (M. Roberts, B. Stewart, and Tingley, 2016b).

$$\theta_d = \alpha + \beta_1 x_{site} + \beta_2 x_{month} + \epsilon \tag{1}$$

Figures 8 and 9 display the regression results.

Figure 8: Regression results 1

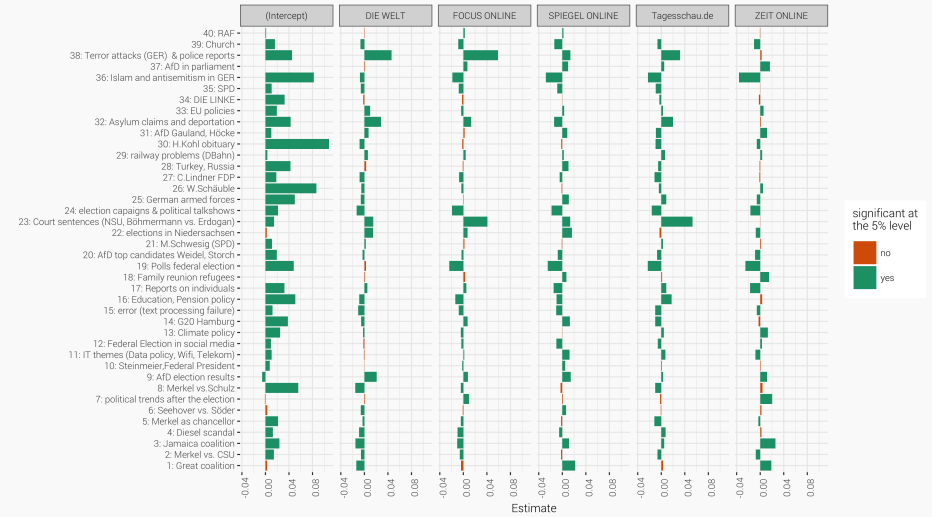
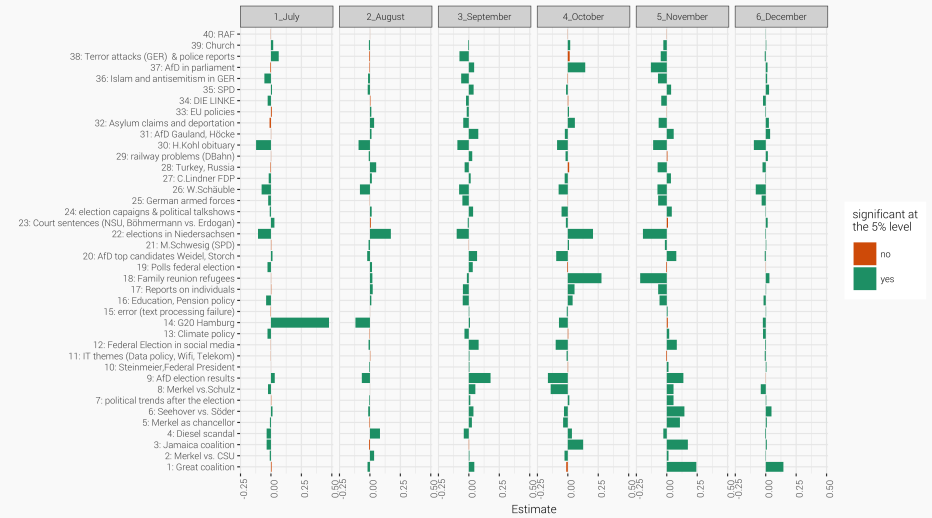


Figure 9: Regression results 2

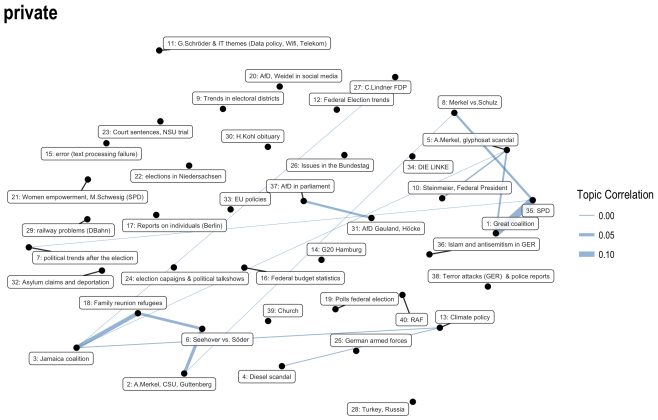


4.2 Topic correlations

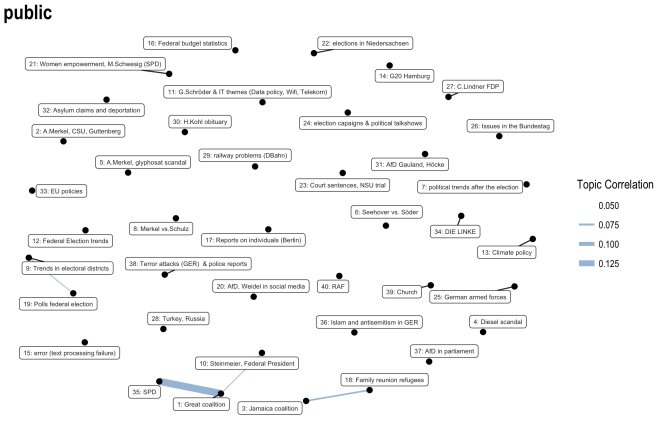
Next, we examine how topics are correlated differently for different news wires, indicating how topics are connected and framed differently in each

newswire. In Figure 10, we find all edges between topics where they exhibit a positive correlation above 0.1 (M. E. Roberts, B. M. Stewart, and E. M. Airoldi, 2016).

Figure 10: Topic Correlation



(a) Private news provider



(b) Public news provider

4.3 Differences in word-topic distributions

Since the word distribution of a topic is a simple mapping of text in space, we can use their word distribution β to compute the similarity. More precisely,

we get a respective β, KxV matrix for each covariate level. We use each row (corresponding to each topic) to calculate the similarity of the word-topic distribution between the news provider using the square root of the Jensen-Shannon (JS) Divergence. Jensen-Shannon Divergence is a positive definite measure, satisfying the following conditions: $D_{js}(a,b) \geq 0$, $D_{js}(a,b) = 0$ iff $(a = b)$. It is also symmetric: $D_{js}(a,b) = D_{js}(b,a)$. Let $p(x)$ and $q(x)$ be two probability density functions, the Jensen-Shannon distance $D_{js}(p,q)$ between this two distributions is defined as:

$$D_{js}(p,q) = \frac{1}{2}D_{KL}(p, \frac{p+q}{2}) + \frac{1}{2}D_{KL}(q, \frac{p+q}{2})$$

where D_{KL} is the Kullback-Leibler divergence between p and q defined as:

$$D_{KL}(p,q) = \sum_{i=1}^{T} p_i ln \frac{p_i}{q_i}$$

So $D_{js} \to 0$ indicates stronger similarities. Since D_{js} does not satisfy the triangular inequality condition $D_{js}(a,c) \leq D_{js}(a,c) + D_{js}(b,c)$, the JSD is not considered to be a real metric. However, we can use the square root of JSD as a real distance metric (Endres and Schindelin, 2003). We will compare this metric with a set of other similarity measures recently used in the literature to measure the difference between word-topic distributions.

(M. Roberts, B. Stewart, and Tingley, 2016a): They use the L_1 norm of the word-topic distributions to compare topics from different models. The L_1 norm is the sum of the absolute value of the difference between two vectors. Its defined as

$$L_1 = \sum_{v} |\beta_{kvi} - \beta_{kvj}|$$

where i and j indicate different covariate levels. This measure has a range of $[0, 2]$, where $L_1 \to 0$ indicates strong similarities. They compare this measure with a cosine similarity metric, which is essentially the dot product rescaled by the L_2 norm of the vectors and is defined as

Again, i, j indicate different covariate levels. However, different to the above mentioned metrics the cosine similarity has a range of $[0, 1]$ and $cos(\theta) \rightarrow 0$ indicate less similarity.

Figure 11 displays the different distance measures

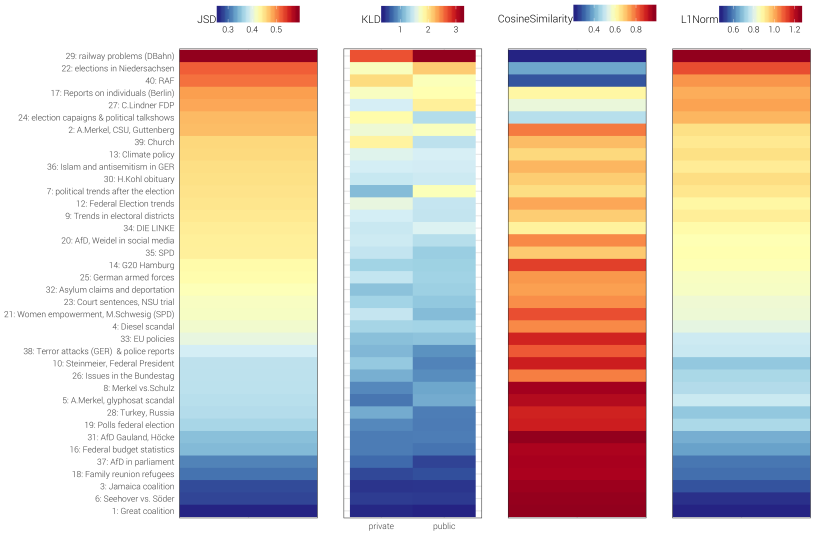


Figure 11: Similarity measures of word-topic probabilities

Appendix

check topics that are most different