CESifo Working Papers

8943
2021

March 2021

Selective Sharing of News Items and the Political Position of News Outlets

Julian Freitag, Anna Kerkhof, Johannes Münster

CESifo

Impressum:

CESifo Working Papers
ISSN 2364-1428 (electronic version)
Publisher and distributor: Munich Society for the Promotion of Economic Research - CESifo GmbH
The international platform of Ludwigs-Maximilians University's Center for Economic Studies and the ifo Institute
Poschingerstr. 5, 81679 Munich, Germany
Telephone +49 (0)89 2180-2740, Telefax +49 (0)89 2180-17845, email office@cesifo.de
Editor: Clemens Fuest
https://www.cesifo.org/en/wp
An electronic version of the paper may be downloaded
· from the SSRN website: www.SSRN.com
· from the RePEc website: www.RePEc.org
· from the CESifo website: https://www.cesifo.org/en/wp

CESifo *Working Paper No. 8943*

Selective Sharing of News Items and the Political Position of News Outlets

Abstract

We present a new measure for the political position of news outlets based on politicians' selective sharing of news items. Politicians predominantly share news items that are in line with their political position, hence, one can infer the political position of news outlets from the politicians' revealed preferences over news items. We apply our measure to twelve major German media outlets by analyzing tweets of German Members of Parliament (MPs) on Twitter. For each news outlet under consideration, we compute the correlation between the political position of the seven parties in the 19th German Bundestag and their MPs' relative number of Twitter referrals to that outlet. We find that three outlets are positioned on the left, and two of them are positioned on the right. Several robustness checks support our results. We also apply our procedure to nine major media outlets from the USA and find that two outlets are positioned on the right, five are positioned on the left of the political spectrum.

JEL-Codes: H410, L820, L860, P160.

Keywords: political media bias, political position, selective sharing, social media, Twitter.

Julian Freitag
freitag.julian@gmail.com

Anna Kerkhof
ifo Institute – Leibniz Institute for Economic Research at the University of Munich / Germany
kerkhof@ifo.de

Johannes Münster
University of Cologne / Germany
johannes.muenster@uni-koeln.de

February 25, 2021
We thank our editors Luis Aguiar and Kenneth Wilbur, two anonymous referees, Maja Adena, Kai Barron, Felix Bierbrauer, Marcel Garz, Julian Harke, Erik Hornung, Steffen Huck, Ulrich Kaiser, and participants of the 4th Workshop on the Economics of Media Bias at WZB Berlin 2019 for helpful comments and suggestions. Nikola Noske, Sarah Recht, and Leja Riedl provided excellent research assistance. Anna Kerkhof acknowledges funding from the Joachim-Herz-Stiftung. Funded by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) under Germany‘s Excellence Strategy - EXC 2126/1-390838866. All errors are our own.

1. Introduction

State-of-the-art research shows that the media have a causal effect on the economic and political choices of individuals (DellaVigna and La Ferrara, 2016). The media are, however, repeatedly accused of being biased towards the political left or right. For instance, six-in-ten US citizens see political bias in the news media[1] and four-in-ten German voters think that the government exerts pressure on the media.[2] Are the media really biased? A growing body of literature addresses these questions by developing methods to assess political biases of news outlets (Groeling, 2013; Puglisi and Snyder, 2016).

Measuring the political position of news outlets is challenging, though. In particular, researchers must find ways to overcome problems of subjectivity and the absence of suitable baselines against which to assess bias (e.g., Groeling, 2013). Existing approaches are based on in-depth content analyses – either by human or by automated coding – or on determining the political position of the news outlets' audience (Puglisi and Snyder, 2016). Many of these procedures are data demanding, computationally burdensome, and time consuming. Easy to implement methods to assess the political position of news outlets, in contrast, are rare.

We present a novel approach to measure the political position of online news outlets that is based on the selective sharing of news items by politicians on social media.[3] Our central argument is that politicians predominantly share news items that are in line with their own political position, i.e., left-wing politicians prefer to share news items from left-wing news outlets, while right-wing politicians prefer to share news items from right-wing news outlets.[4] Consequently, we can utilize the politicians' revealed preferences over news items to infer the political position of the news outlets.[5]

In an application to Germany, we compute a Spearman rank correlation coefficient for each news outlet under consideration. The Spearman rank correlation coefficient measures the correlation between the rank of the political position of the politicians' parties (from most left-wing to most right-wing on a one-dimensional scale) on the one hand, and the rank of the politicians' share of referrals to a particular news outlet – aggregated on the party level – on the other hand. A positive correlation indicates that the news outlet is positioned on the right, a negative correlation indicates that the news outlet is positioned on the left.

Our approach has several advantages. First, in comparison to existing approaches, it

[1] See `https://news.gallup.com/poll/207794/six-partisan-bias-news-media.aspx`, viewed: Feb 2019.

[2] See `https://docplayer.org/43364962-Glaubwuerdigkeit-der-medien-eine-studie-im-auftrag-des-westdeutschen-rundfunks-dezember-2016.html`, viewed: Feb 2019.

[3] Our definition of news items includes every piece of information that news outlets publish (e.g., news and opinion articles, short and breaking news, videos, pictures, illustrations, and press releases). We also report results by newspaper section.

[4] A robustness check to the application of this measure confirms that less than four percent of the politicians' referrals criticize the news item or the news source.

[5] Note that we do not use the term "media slant." Media slant often refers to news outlets' choice of language as, e.g., in the seminal paper by Groseclose and Milyo (2005). Our approach, in contrast, does not distinguish between slanted language and other potential forms of media bias.

is relatively quick and easy to implement. We infer the political position of news outlets from the selective sharing of news items by politicians, whose political position is clear. Moreover, since sharing news items on social media is nowadays part of the politicians' profession, we observe the politicians' choices over news items in a setting where they have an incentive to reveal their preferences consciously and truthfully. Thus, our approach does not require any elaborate content analysis, but circumvents problems of subjectivity and the absence of suitable baselines against which to assess bias nonetheless. Second, the results from our procedure are straightforward to interpret. The Spearman rank correlation coefficient for a particular news outlet is either positive, negative, or equal to zero, whereby the news outlet can directly be classified as positioned on the left, on the right, or in the center of the political spectrum. Finally, our approach is applicable widely beyond this paper. In particular, while many existing procedures are limited to assessing political media bias in two-party democracies, our approach can also be applied to multi-party democracies, as long as the parties' political position can be measured on an ordinal, one-dimensional scale.[6] In addition to that, our approach is not data demanding and can thus be applied to small datasets, too.

We apply our procedure to twelve major online news outlets in Germany and consider the selective sharing of news items of German MPs on Twitter. The Spearman rank correlation coefficient is positive for five news outlets, but only statistically significant for two of them (*BILD* and *Welt*). The Spearman rank correlation coefficient is negative for seven further news outlets, and statistically significant for three of them (*Zeit*, *Spiegel*, and *Deutschlandfunk*). Following the above considerations, we conclude that *BILD* and *Welt* are positioned on the right, *Zeit*, *Spiegel*, and *Deutschlandfunk* are positioned on the left, and the remaining seven news outlets are positioned in the center of the political spectrum. Several robustness checks support our main results.

In an extension, we also analyze the selective sharing of news items of Members of the US Congress; this is particularly interesting, as reliable information on the *individual* political position of Congress Members – in terms of ADA Scores[7] – is available. Computing the correlation between individual political position and individual Twitter referral shares to nine major news outlets, we find that *CNN*, *NYTimes*, *NBC*, *Washington Post*, and the *LA Times* are positioned on the left, *Wall Street Journal* and *Fox News* are positioned on the right, and *ABC* and *USA Today* are positioned in the center of the political spectrum. Moreover, we show that our results are highly correlated to the measures obtained in the seminal papers of Groseclose and Milyo (2005) and Gentzkow and Shapiro (2010).

The remainder of the paper is organized as follows. Section 2 discusses the related literature. Section 3 illustrates the application of the Spearman rank correlation coefficient as a measure of the political position of news outlets more closely. In Section 4, we describe the data collection procedure and the data preparation process. Section 5 presents the

[6]Machine learning techniques, for instance, usually struggle when multiple parties are involved (Colleoni et al., 2014).

[7]See Appendix C for further information.

results of our application and compares them to existing measures of the political position of German news outlets. Section 6 demonstrates the robustness of our results by checking the tonality of the tweets, excluding extreme parties from the analysis, and by considering different numbers of news outlets. Moreover, we demonstrate that our results hold when we consider tweets by German MPs from a different time period and when we compute the political position of news outlets based on the selective sharing of news items by German Members of the European Parliament and Members of the German State Parliaments. Section 7 concludes.

2. Related literature

Our paper is related to three strands of literature. First, our approach to measure the political position of news outlets contributes to the literature on political media bias (see Groeling, 2013; Gentzkow et al., 2016; Puglisi and Snyder, 2016, for surveys). It is especially close to papers that develop alternative methods to measure political bias of news outlets in the US (e.g., Groseclose and Milyo, 2005; Ho and Quinn, 2008; Gentzkow and Shapiro, 2010) and in Germany (e.g., Dallmann et al., 2015; Dewenter et al., 2016; Garz et al., 2020). We contribute to this literature by presenting a novel approach to determine the political position of news outlets that is easy to implement, straightforward to interpret, and applicable to multi-party democracies and small datasets.

Next, our paper is related to the growing literature on the selective sharing of information on social media. This literature is divided into two fields. One group of papers infers the political position of users *from* their selective sharing of information with a clear political position(e.g., Barberá et al., 2015; Boutet et al., 2012; Colleoni et al., 2014). A second group of papers takes the reverse approach and provides *evidence of* the selective sharing of information by users whose political position is clear. Adamic and Glance (2005), for instance, demonstrate that political bloggers prefer to share hyperlinks that match their own political opinion. In addition, Shin and Thorson (2017) and Aruguete and Calvo (2018) show that Twitter users selectively share messages that are in line with their political position; An et al. (2014) provide analogous evidence for selective sharing on Facebook. Our approach builds on the findings from the latter group of papers, since our measure is based on politicians' selective sharing of news items that are in line with their own political position.

Finally, we contribute to studies that examine the role of social media in political processes (Luca, 2016, provides a survey on the economic and political impact of social media and user-generated content). The selective exposure to social media content has attracted particularly much attention (e.g., Bakshy et al., 2015; Knobloch-Westerwick and Meng, 2009, 2011; Garrett, 2009a,b). Selective exposure to social media content is conceptually closely related to selective sharing of information; the two are complementary processes (Shin and Thorson, 2017). Related to our approach is the paper by An et al. (2012) who create a one-dimensional map of the political position of US news media based on Twitter users' subscription and interaction patterns.[8] On top of that, our paper adds to studies on politicians' usage of Twitter and other social media (Jungherr, 2016), coverage of politicians on Twitter (Jungherr, 2014), and the contribution of social media in political mobilization (Bond et al., 2012) and social movements (Hermida et al., 2014).

3. Method

As argued, the idea of the approach is to assess the correlation between the political position of a party and its politicians' number of referrals to a specific news outlet. As reported in Laver (2014), different estimates of the positions of political parties in Germany tend to be correlated, but also exhibit substantive differences. We therefore trust the parties' *ranking* on a left-right scale more than a precise numerical estimate that might hinge on the method used to obtain it (e.g., whether it builds on expert surveys or on comparisons of party manifestos) and employ the *Spearman rank correlation coefficient*[9], a well known non-parametric measure of the correlation between two ordinal variables.[10]

Regarding our application to the selective sharing of news items of German MPs on Twitter, let o, $o = 1, ..., 12$, denote the twelve news outlets under consideration (see Section 4 for details on the selection process). Moreover, let i, $i = 1, ..., 7$, denote the seven parties in the 19th Bundestag. The political position of party i is denoted by $x_i \in \mathbb{R}$.[11] Let n_{io} denote the absolute number of tweets from MPs of party i that contain a reference to outlet o. These raw counts will depend on the number of MPs belonging to party i and on how active they are on Twitter, two factors that are not informative about the political position of outlet o. Therefore, our main measure considers the *relative* number of Twitter referrals by party i to outlet o,

$$y_{io} = \frac{n_{io}}{\sum_{r=1}^{12} n_{ir}}. \tag{1}$$

We observe seven different values y_{io} – one for each party i – for each news outlet o.[12]

Next, the parties' political positions, x_i, are assigned to integer ranks $rg(x_i)$, where

[8]The intuition is that the closer the political position of two media sources, the more their audiences overlap.

[9]See Siegel and Castellan (1988), for a detailed discussion on the Spearman rank correlation coefficient.

[10]As a robustness check, we also computed the Neymann Pearson correlation coefficient between the referral shares to each news outlet and two different *point estimates* for the parties' political position, taken from Forschungsgruppe Wahlen (2017) and infratest dimap (2015), respectively. The correlation between the estimates of the news outlets' political position from the robustness checks and the main estimates in Section 5.1 is large: it is equal to 0.985 when we use the data from Forschungsgruppe Wahlen (2017), and equal to 0.991 when we use infratest dimap (2015).

[11]By aggregating tweets on the party level, we abstract from political heterogeneity within parties. This simplification makes our analysis less data demanding. If the political position of the MPs who share news items on Twitter deviates from the political position of their parties, however, the MPs' selective sharing of news items may not be informative about the political position of news outlets. Appendix B discusses such concerns and shows they are likely of minor importance in our setting.

[12]Of course, considering the relative number of Twitter referrals y_{io} rather than the absolute numbers n_{io} involves a loss of information. It is crucial to normalize by the total number of referrals, however, to filter out cross-party differences in Twitter activity. See Section 6 for a discussion of the advantages and disadvantages of using the relative number of Twitter referrals.

rank 1 is given to the most left-wing, and rank 7 is given to the most right-wing party. Moreover, fix a news outlet o and consider the relative numbers of Twitter referrals y_{io} by parties $i = 1, ..., 7$ to this news outlet o. Assign integer ranks $rg(y_{io})$ from rank 1 to rank 7, where the smallest referral share to news outlet o is given the smallest rank.[13] For outlet o, let ρ_o denote the correlation coefficient between $rg(x_i)$ and $rg(y_{io})$. It is given by

$$\rho_o = \frac{\sum_{i=1}^{7}(rg(x_i) - \overline{rg(x)})(rg(y_{io}) - \overline{rg(y_o)})}{\sqrt{\sum_{i=1}^{7}(rg(x_i) - \overline{rg(x)})^2}\sqrt{\sum_{i=1}^{7}(rg(y_{io}) - \overline{rg(y_o)})^2}}, \tag{2}$$

where $\overline{rg(x)}$ and $\overline{rg(y_o)}$ denote the average ranks of x and y for outlet o (in our application $\overline{rg(x)} = \overline{rg(y_o)} = 3.5$). In other words, equation (2) gives the Spearman rank correlation coefficient between the political position of a party and the relative number of Twitter referrals from this party mentioning outlet o.

The values of ρ_o lie in the interval $[-1, 1]$. If $\rho_o > 0$, the parties' ranked political position and their respective ranked relative number of Twitter referrals to outlet o are *positively* correlated. Thus, news items from o are shared relatively more often by right-wing MPs, which indicates that news outlet o is positioned on the right of the political spectrum. If, on the other hand, $\rho_o < 0$, the parties' ranked political position and their respective ranked relative number of Twitter referrals to outlet o are *negatively* correlated. Thus, news items from o are shared relatively more often by left-wing MPs, which indicates that outlet o is positioned on the left of the political spectrum. Finally, if $\rho_o = 0$, the parties' ranked relative number of Twitter referrals to outlet o is independent from their political position; in this case, news outlet o is positioned in the center of the political spectrum.

The magnitude of ρ_o corresponds to the size of the correlation between the parties' ranked political position and their respective ranked relative number of Twitter referrals to news outlet o, given the parties and the news outlets under consideration. Thus, a positive (negative) value of ρ_o indicates that items by news outlet o are shared more often by right-wing (left-wing) parties, and the larger the absolute value of ρ_o, the more is news outlet o preferred by right-wing (left-wing) parties. A correlation coefficient equal to 0.1, for instance, would correspond to a small, a correlation coefficient equal to 0.3 would correspond to a medium, and a correlation coefficient equal to 0.5 would corresponds to a large effect (Cohen, 1988, Ch.3.2).[14]

We test the statistical significance of ρ_o against the null hypothesis that $rg(x_i)$ and $rg(y_{io})$ are independent, i.e., we test

H_0: *There is no correlation between the parties' ranked political position and their ranked referral shares to outlet o.*

against

[13]Note that the ranks are based on the *population* of all tweets from a particular time period and not on a sample of tweets. A potential concern is that the observation period is not representative for other points in time; see Section 6.4 for a discussion.

[14]See Section 6.3 for a discussion on why the magnitude of ρ_o may depend on the selection of news outlets.

H_1: *There is a correlation between the parties' ranked political position and their ranked referral shares to outlet o.*

Given the small number of observations per news outlet o ($N = 7$), we consider the exact p-values of the Spearman rank correlation coefficients ρ_o, which we take from Owen (1962).[15] Since we test H_0 for twelve news outlets, we also take multiple hypotheses testing into account with the Bonferroni correction.

4. Data

To carry out the analysis, we first determine which news outlets to consider. Our approach is based on the assumption that the selective sharing of news items reveals politicians' preferences over the news outlets' content. Hence, a major requirement on the news outlets is that all German MPs can potentially select from all outlets' news items. Local and specialized news outlets (i.e., those that focus on a particular topic such as sports, fashion, or economics) are thus excluded from the analysis.[16] Moreover, we do not consider news aggregators such as Google news or mixed content providers such as e-mail providers. We retrieve the ten largest national online news outlets (by number of visits) from `ivw.de`.[17] Nine out of these ten news outlets meet the requirements discussed above.[18] In addition, we include the online news sites of the two major German public TV broadcasters and the major German public radio news broadcaster into the analysis, such that we end up with twelve national online news outlets.[19]

Next, we collect tweets from all MPs of the seven parties in the 19^{th} Bundestag (2017–) who are active on Twitter via the Twitter API. In a first step, we retrieve every tweet by every MP between Oct 24, 2017 (first session of the newly elected Bundestag), and May 11, 2018.[20] Next, we check which tweets share news items published by one of the twelve selected online news outlets, where news items correspond to every piece of information

[15] The idea of the exact p-values is as follows (see also Siegel and Castellan, 1988, p.242). For any N, the Spearman rank correlation coefficient can only take on a discrete number of values. If $N = 2$, the Spearman rank correlation coefficient ρ can take on the values $+1$ and -1, both of which have probability 1/2 under H_0. If $N = 3$, ρ can take on the values -1, $-1/2$, $+1/2$, and $+1$, with probabilities 1/6, 1/3, 1/3, and 1/6 under H_0, respectively. For small N, it is thus possible to obtain the probabilities under H_0 for all possible values of ρ and to compute the exact p-values for the observed values of ρ on that basis. In our application, $N = 7$ for all news outlets o, which is sufficiently small to obtain exact p-values. Note, moreover, that the constant number of observations per news outlet implies that we obtain identical p-values for identical estimates of ρ_o.

[16] See Section 7 for a discussion on how to apply the approach to local news outlets.

[17] The IVW ("Information Community for the Assessment of the Circulation of Media") certifies and audits the circulations of major publications, including newspapers and magazines, within Germany.

[18] We excluded *upday* from the analysis, which is a news aggregator pre-installed on all Samsung mobile devices.

[19] The top ten news outlets by number of visits include all major German national news outlets. Technically, our analysis could be extended to more online news outlets. The smaller the news outlet, however, the less likely it is to meet the requirements.

[20] For our robustness checks in Sections 6.4 and 6.5, we retrieve every tweet by every Member of Federal Parliament (Bundestag), by every German Member of the European Parliament, and by every Member of one of the sixteen German State Parliaments between Dec 27, 2018, and July 15, 2019. The subsequent steps of the analysis remain the same.

that news outlets publish, including news and opinion articles, short and breaking news, videos, pictures, illustrations, and press releases. We aggregate the absolute numbers of Twitter referrals on the party level (Table 1).[21] While none of the parties tweets only rarely, Table 1 shows that there are clear differences in the number of tweets across parties. The corresponding relative numbers of Twitter referrals to each outlet for each party are displayed in Table 2.

Finally, for each outlet o, we assign the ranks 1 to 7 to the seven parties referral shares to o, where rank 1 is given to the smallest, and rank 7 to the largest referral share. For the ranking of the political parties we rely on Forschungsgruppe Wahlen (2017) who order the parties from left to right in the political spectrum. An overview of all ranks is given in Table 3.

5. Results

5.1. Main results

Table 4 shows the results from computing the Spearman rank correlation coefficient ρ_o for all twelve news outlets. We find that ρ_o is positive for five news outlets, but only statistically significant for two of them (*BILD* and *Welt*). Moreover, we find that ρ_o is negative for seven further news outlets and statistically significant for three of them (*Zeit*, *Spiegel*, and *Deutschlandfunk*). Hence, following our considerations from Sections 1 and 3, we conclude that *BILD* and *Welt* are positioned on the right, *Zeit*, *Spiegel*, and *Deutschlandfunk* are positioned on the left, and the remaining seven news outlets are positioned in the center of the political spectrum.[22]

The magnitudes of ρ_o unveil further insights. While the absolute value of ρ_o is close to 1 and thereby indicates a close to perfect monotone relationship between the parties' ranked political position and their respective ranked relative number of Twitter referrals for *Zeit*, *BILD*, and *Welt*, the relationship is slightly less pronounced for *Spiegel* and *Deutschlandfunk*. In other words, *Zeit*, *BILD*, and *Welt* are more clearly positioned on the left or right of the political spectrum than *Spiegel* and *Deutschlandfunk*. Note, moreover, that the absolute values of ρ_o for *Focus* on the right, and for *SZ*, *ARD*, and *ZDF* on the left of the political spectrum are considerable, too ($\rho_o > 0.5$). The lack of statistical significance for these outlets is in part reminiscent of the small number of observations per outlet ($N = 7$); to achieve statistical significance at the 5%-level for *ARD* and *ZDF*, for instance, we would need at least 10 observations (i.e., ten parties) per outlet.[23]

We stress that our results are estimates of a correlation, and an interpretation in terms of, e.g., marginal effects is not viable. A larger absolute value of ρ_o corresponds to a

[21] This includes reactions and comments on re-tweets that originally shared news items. Some illustrative examples are displayed in Appendix A.

[22] Under the Bonferroni correction, ρ_o is statistically significant (5% level) for three news outlets: *BILD*, *Welt*, and *Zeit*.

[23] Note also that the magnitude of ρ_o may depend on the selection of news outlets o; see Section 6.3 for further discussion.

larger correlation of the ranks of the political parties on the one hand and the ranks of the outlet's referral shares on the other, which we interpret as having a more pronounced political position. Interpreting the differences between the numerical values of ρ_o for different news outlets is not very informative, however.

5.2. Results by news outlet section

Next, we compute the Spearman rank correlation coefficient ρ_o by news outlet section.[24] While Section 5.1 presents the average political position of a news outlet, computing the Spearman rank correlation coefficient by news outlet section yields more fine-grained results: the political position of a news outlet may differ between sections; similarly, some sections might not exhibit a political position at all. In particular, we expect our results to be more clear-cut when we focus on referrals to "political" sections such as politics or business, and to be more ambiguous when we focus on "non-political" sections such as feuilleton, sports, and knowledge.

Table 4 shows the results. When we consider only referrals to the news outlets' politics section (*Politics*), we find that ρ_o is positive for four news outlets and statistically significant for two of them (*BILD* and *Welt*). Moreover, we find that ρ_o is negative for six further outlets and statistically significant for five of them (*Zeit*, *Spiegel*, *SZ*, *Stern*, and *ARD*). Hence, we conclude that the politics sections of *BILD* and *Welt* are positioned on the right, the politics sections of *Zeit*, *Spiegel*, *SZ*, *Stern*, and *ARD* are positioned on the left, and the politics sections of the remaining two outlets are are positioned in the center of the political spectrum.[25] The absolute values of ρ_o remain within the same order of magnitude relative to Section 5.1.[26]

When we consider only referrals to the news outlets' business sections (*Business*), we find that ρ_o is positive for four news outlets and statistically significant for three of them (*BILD*, *Welt*, and *F.A.Z.*). Moreover, we find that ρ_o is negative for five further outlets and statistically significant for three of them (*Spiegel*, *SZ*, and *ARD*). Thus, we conclude that the business sections of *BILD*, *Welt*, and *F.A.Z.* are positioned on the right, the business sections of *Spiegel*, *SZ*, and *ARD* are positioned on the left, and the remaining three business sections are positioned in the center of the political spectrum.[27] The absolute value of ρ_o decreases for *Zeit* and *Focus* and increases for *F.A.Z.*, while the remaining news outlets are nearly unaffected.

Finally, when we consider only referrals to the news outlets' feuilleton, sports, and

[24] For ten news outlets, it is possible to infer the section where a news item has been published from its URL (e.g., "`spiegel.de/politik`"); *ZDF* and *Deutschlandfunk* publish all articles under their main domain. *Stern* does not have a separate business section, *ARD* does not have separate feuilleton, sports, and knowledge sections. Note that considering a smaller number of news outlets than in Section 5.1 may also affect the Spearman rank correlation coefficient; see Section 6.3 for further discussion.

[25] Under the Bonferroni correction, ρ_o is only statistically significant (5% level) for *Welt*.

[26] I.e., coefficients that could formerly be classified as "large" according to Cohen (1988) remain large, while the coefficient for *Stern* even increases from "medium" to "large."

[27] Under the Bonferroni correction, no correlation coefficient is statistically significant.

knowledge sections (*Other*)[28], we find that ρ_o is positive for six news outlets and statistically significant for two of them (*Welt* and *Focus*). Moreover, we find that ρ_o is negative for three outlets and statistically significant for two of them (*Zeit* and *Spiegel*). We conclude that the feuilleton, sports, and knowledge sections of *Welt* and *Focus* are positioned on the right, *Zeit* and *Spiegel* are positioned on the left, and the remaining four outlets are positioned in the center of the political spectrum.[29] The absolute value of ρ_o decreases for the majority of news outlets. A notable exception is *Focus*, whose Spearman rank correlation coefficient is close to 1.

The results by news outlet section are intuitive. When we consider only referrals to the news outlets' politics section, we find that more news outlets exhibit a clear political position than when we consider referrals to the entire outlets as in Section 5.1. Similarly, when we limit our attention to referrals to the non-political sections feuilleton, sports, and knowledge, we find that a smaller number of news outlets exhibits a clear political position than in Section 5.1.[30]

5.3. Comparison to existing measures

The political position of German news outlets has been measured before; recent approaches include Dallmann et al. (2015), Dewenter et al. (2016), and Garz et al. (2020). In this section, we demonstrate that the results from our novel approach are similar to the findings from these papers, which supports the validity of our analysis.

Using automated text analysis, Dallmann et al. (2015) develop several distinct measures for political media bias in the politics and economics sections of four online news outlets, including three of whom we consider, too. Regarding the amount of coverage, the authors find that *F.A.Z.* tends to favor the more right-wing parties CDU, CSU, and FDP, while the results for *Spiegel* and *Zeit* are ambiguous (p.136). Regarding the usage of key terms from party manifestos, Dallmann et al. (2015) find that the language of *F.A.Z.* is more similar to CDU and FDP, while *Spiegel* and *Zeit* show higher similarities to the left-wing parties SPD, Greens, and Left (p.137). This matches our result that *F.A.Z.* – especially the business section (see Section 5.2) – is more right-wing than *Spiegel* and *Zeit*, and that *Spiegel* and *Zeit* are positioned on the left of the political spectrum and similar in their political position.

Dewenter et al. (2016) introduce a political coverage index (PCI) that is based on human coding of the tonality of media reports about Germany's two major parties, the center-right CDU/CSU and the center-left SPD.[31] As in our case, values of the PCI lie in the interval $[-1, 1]$, where negative values of the PCI indicate a bias to the left and positive

[28]We pooled these sections, because the number of Twitter referrals to each of them is small.

[29]Under the Bonferroni correction, no correlation coefficient is statistically significant at the 5%-level; ρ_o is only weakly statistically significant (10% level) for *Focus*.

[30]It also matches the public perception of *F.A.Z.* that its business section is positioned on the right on the political spectrum, while its remaining sections are positioned in the center. See, e.g., `https://www.deutschland.de/de/topic/wissen/ueberregionale-zeitungen`. Viewed: March 2020.

[31]The authors use tonality data from MediaTenor.

values indicate a bias to the right. The analysis by Dewenter et al. (2016) includes nine news outlets that we cover, too.[32] We would not necessarily expect the PCI to be perfectly correlated with our measure, because the PCI is obtained by a different method and relies on a comparison of the two major parties only. Figure 1 shows that the values of the PCI are strongly correlated to our Spearman rank correlation coefficient (correlation of 0.77, $p = 0.015$). Moreover, the measures agree on the direction of biases in eight out of nine cases. The only exception is *Stern*, which we classify as positioned in the center of the political spectrum (but with a negative sign), while Dewenter et al. (2016) find that its position is relatively far on the right.

Garz et al. (2020) construct an index of media outlets' political position that is based on comparing the language of the Facebook posts of a news outlet with the language of the election programs of Germany's main political parties. Here, too, the index lies in the interval $[-1, 1]$, where negative values indicate a bias to the left and positive values indicate a bias to the right. The analysis by Garz et al. (2020) includes eleven news outlets that we cover, too. Figure 2 shows that the values of their index are strongly correlated to our Spearman rank correlation coefficient (correlation of 0.74, $p = 0.009$). Moreover, the measures agree on the direction of biases in nine out of eleven cases; exceptions are *Stern* and *Welt*. While Garz et al. (2020) also find that *Stern* is positioned in the center of the political spectrum, they obtain a different sign for its position. Moreover, the authors classify *Welt* as positioned in the center of the political spectrum, while the news outlet is clearly positioned on the right of the political spectrum in our analysis.

6. Robustness checks

6.1. Tonality check

In this section, we probe the robustness of our results. First, our analysis is based on the assumption that politicians share only news items that are in line with their own political position. This assumption would be violated if, for instance, politicians shared news items in order to criticize the item itself or the respective news source, or if they disagreed with a re-tweet that originally shared the news item. To support the plausibility of our assumption, we let two Research Assistants read $2,998$ randomly drawn tweets from our dataset.[33] The Research Assistants were asked to determine if a tweet criticizes the shared news item or its outlet, if it criticizes the content of a re-tweet that shared a news item, if it criticizes the news item or its news outlet in a re-tweet, or if it does not contain any of these criticisms. Appendix A displays some illustrative examples of tweets that the Research

[32] Dewenter et al. (2016) analyzed two different news sources by ARD and ZDF, respectively. We used the mean values of the PCI for these news outlets to conduct the comparison.

[33] We initially decided that the Research Assistants could code $3,000$ tweets within a reasonable amount of time. The random tweets were drawn proportionally to the total amount of tweets. E.g., if the Twitter referrals of party i to news outlet o constituted 1% of all tweets, we would randomly draw $1\% * 3,000 = 30$ tweets by party i to news outlet o for the Research Assistants to check. Rounding of non-integer numbers of tweets resulted in $2,998$ instead of $3,000$ tweets.

Assistants classified as criticizing or non-criticizing. In sum, 113 tweets – i.e., 3.8% – were classified as criticizing (inter coder reliability of 99%). This small fraction supports the plausibility of our basic assumption that the MPs share news items via Twitter that are in line with their own political position.

As a further robustness check, we excluded these 113 criticizing tweets from the randomly drawn subsample of $2,998$ tweets and computed the Spearman rank correlation coefficient on the basis of the remaining $2,885$ tweets. Since the random subsample was drawn proportionally to the entire sample, the referral shares y_{io} – and thereby the Spearman rank correlation coefficient ρ_o – can only be affected if these criticizing tweets are unproportionally distributed across parties *and* outlets; otherwise, our results would remain unchanged.[34] The first row of Table 5 shows that although the magnitude of the Spearman rank correlation coefficient underlies small changes compared to the results shown in Table 4, our main results are robust to taking out the criticizing tweets. In addition, ρ_o is weakly statistically significant (10% level) for two further outlets: *Focus* and *ARD*, where the former is positioned on the right, and the latter is positioned on the left of the political spectrum.

Another concern could be that a left-leaning politician might endorse a left-leaning article from a right-leaning outlet. Such tweets would not be classified as criticizing in our data and one might worry whether they induce some measurement error. Such tweets reveal, however, that some of the news outlet's content is in fact in line with the left-leaning politician, and these revealed preferences should be taken into consideration when determining the news outlet's political position. Thus, while these tweets might affect our results, they do not introduce measurement error; rather, they capture some inherent properties of the news outlets under consideration.

6.2. Exclude extreme parties

Next, we confirm that our approach does not hinge on the selective sharing of the politically extreme parties, LINKE and AfD, alone. It is, for instance, possible that only these parties follow distinct patterns in their sharing behavior, while the sharing behavior of the more centrist parties is similar and thereby uninformative about the political position of the news outlets.[35] To this end, we exclude (i) LINKE, (ii) AfD, and (iii) LINKE and AfD at the same time from the analysis and compute the Spearman rank correlation coefficient based on the relative number of Twitter referrals by the remaining parties, respectively.

[34] For instance, if only a particular party criticizes all news outlets, but does so proportionally across outlets such that for all outlets the same fraction of tweets is critical, its relative number of Twitter referrals is not affected when dropping those negative tweets. Similarly, if only a particular news outlet is being criticized, but proportionally so by all parties, the ranking within that outlet would not be affected, either.

[35] On the other hand, it has recently been argued that the extremely left-wing and the extremely right-wing parties have become quite similar regarding certain topics such as immigration; see, e.g., `https://www.zeit.de/politik/deutschland/2017-07/afd-linke-rechts-links-waehler-gemeinsamkeiten`, viewed Feb 2019. If this was the case, our main results would even be too conservative.

Rows two, three, and four of Table 5 show the results. The absolute values of the Spearman rank correlation coefficient underly small changes compared to the results shown in Table 4, but largely remain within the same order of magnitude. Moreover, given the smaller number of observations ($N = 6$ in rows two and three, $N = 5$ in row four), our results are less statistically significant. While ρ_o is statistically significant for *BILD*, *Welt*, and *Zeit* in all three analyses, it is not statistically significant for *Spiegel* and *Deutschlandfunk* when excluding AfD (row three) or both AfD and LINKE (row four).

6.3. Relative number of Twitter referrals

Our approach uses the parties' *relative* number of Twitter referrals to each of the twelve news outlets as a basis for their ranking (see Section 4). The major advantage over using the absolute number of Twitter referrals is that the parties who are most active on Twitter are not automatically given high referral ranks for each news outlet, which would undermine the idea of our measure. The main disadvantage of this approach is, however, that the Spearman rank correlation coefficient that we compute for each outlet is dependent on the other news outlets included into the analysis, because a party's referral share to news outlet o – and thereby its rank – depends on the referrals to all other news outlets that we consider.

We consider this to be a minor disadvantage; three robustness checks support this view. First, we included Twitter referrals to *taz*, which is known to be a very left-wing news outlet, into the analysis (Table 5, row five).[36] News items by *taz* are relatively often shared by left-wing, but not by right-wing parties; as a result, the referral shares to the original twelve outlets change for the left-wing, but not for the remaining parties. Accordingly, we find that ρ_o decreases for *Zeit*, but is still statistically significant at the 1% level. Moreover, ρ_o for *taz* itself is negative and also statistically significant at the 1%-level, hence, *taz* is positioned on the left as expected. The results for the remaining news outlets are unaffected.

Second, we successively exclude the Twitter referrals to one of the originally selected twelve news outlets and check how the results for the remaining eleven news outlets change.[37] In each case, the magnitude of the Spearman rank correlation coefficient changes slightly, but never switches sign. Moreover, with one exception, the news outlets that are classified as positioned on the political left or right in Section 5.1 remain to be classified as such unless it is their turn to be excluded (the exception is that when we exclude *Welt*, ρ_o for *Deutschlandfunk* is no longer statistically significant).

Third, we compare our results from Section 5.1 with the results we would have obtained when using the absolute instead of the relative number of Twitter referrals.[38] The most

[36] We did not include *taz* in the main analysis, as it is not among the most visited German news outlets.
[37] These results are unreported, but available upon request.
[38] Using the relative number of referrals to a news outlet also distinguishes our approach from a recent study by the Pew Research Center that classifies the political position of a number of US news outlets based on the absolute number of Facebook shares by members of the 114th and 115th US Congresses. See `http://www.people-press.org/2017/12/18/sharing-the-news-in-a-polarized-congress/`, viewed: Feb

right-wing party AfD – whose members are most active on Twitter – would then be given one of the highest ranks for each news outlet, while the second-most right-wing party CSU – whose members are least active on Twitter – would be given one of the lowest. As a result, the Spearman rank correlation coefficients would be very different from those presented in Table 4 (Table 5, row six). In particular, the magnitude of the coefficients computed based on the absolute number of Twitter referrals is smaller, and none of them is statistically significant.

6.4. Longitudinal analysis

The Spearman rank correlation coefficient is based on the population of tweets from a particular time period. This would be a concern if the tweets from the time period under consideration were not representative for the population of tweets from different points in time. This section shows that our measure remains stable if we consider the tweets from a subsequent time period. To this end, we retrieve all tweets from all German MPs between Dec 27, 2018 and July, 15, 2019, which corresponds to a time window that is as long as the time window in the main analysis but does not overlap with it. Row seven in Table 5 shows that the results based on this alternative set of tweets are very similar to our main results in Table 4. Moreover, Column 1 of Table 6 shows that the measures exhibit a correlation of 0.97.

6.5. Selective sharing of Members of the European Parliament and the State Parliaments

The key idea of this paper is to measure the political position of news outlets by selective sharing of news items on Twitter by politicians. A potential concern is that results might unduly depend on which politicians are taken into consideration. Indeed, if we would get very different results when applying the same methodology to a different set of politicians, one might wonder whether the results are more informative about these politicians rather than about the media. In this subsection, however, we demonstrate that our results from Section 5.1 are robust when we study members of other legislative bodies instead of Members of the Federal Parliament.

To this end, we retrieve all tweets from German Members of the *European Parliament* and from Members of the sixteen German *State Parliaments* between Dec 27, 2018 and July, 15, 2019 (i.e., we use the same time window as in Section 6.4). Rows eight and nine in Table 5 show the results. According to the Twitter referrals of German Members of the European Parliament (row eight), *BILD* and *Welt* are positioned on the right, *Zeit*, *SZ*, and *ARD* are positioned on the left, and the remaining seven news outlets are positioned in the center of the political spectrum. According to the Twitter referrals of Members of the State Parliaments (row nine), *BILD*, *Welt*, *n-tv*, and *Focus* are positioned on the

2019.

right, *Zeit*, *Spiegel*, *ARD* and *ZDF* are positioned on the left, and the remaining four news outlets are positioned in the center of the political spectrum.

The results are similar to what we find when we consider the selective sharing of news items by German MPs during the same time period. Table 6 shows that the measures based on tweets from Members of the European Parliaments and Members of the Bundestag exhibit a correlation of 0.85 and the measures based on tweets from Members of the State Parliaments and Members of the Bundestag exhibit a correlation of 0.89.

7. Conclusion

We present a novel and relatively easy to implement measure for the political position of news outlets that is based on the selective sharing of news items by German MPs. Its application to twelve major German online news outlets shows that two news outlets, *BILD* and *Welt*, are positioned on the right, three news outlets, *Zeit*, *Spiegel*, and *Deutschlandfunk*, are positioned on the left, and the remaining news outlets are positioned in the center of the political spectrum. These results are in line with earlier findings on the political position of German news outlets.

Our approach offers a number of advantages over existing measures. First, the data requirements are modest: we determine the political position of news outlets based on MPs' Twitter referrals, which are relatively quick and easy to obtain from Twitter's API. Existing approaches, in contrast, are typically based on text analyses that require thousands of full-length news articles along with additional datasets such as party manifestos or pre-built dictionaries. To compute the Spearman rank correlation coefficient, however, we just need the MPs' party affiliation and the parties' left-right ranking on an ordinal scale.[39]

Second, our approach solely employs data that is publicly available; in particular, it does not require (costly) access to newspaper databases or archives or any other exclusive dataset.[40] Hence, our analysis could be replicated, extended, or adopted to further applications by any researcher at any time.

Third, our analysis is likely to be less computationally burdensome than existing approaches that determine the political position of news outlets. Once the MPs' Twitter referrals are obtained, the Spearman rank correlation coefficient can be computed within minutes (even manually). This computational ease stands in contrast to text analysis approaches that face the complexity and high dimensionality of text as data.[41]

Our approach is limited in four respects. First, while our approach can assess whether a news outlet is positioned on the left or on the right, it is agnostic about the type of

[39] Dallmann et al. (2015), for instance, use more than 130,000 articles with over 62,000,000 words; Garz et al. (2020) downloaded more than two million Facebook posts. Both approaches involve additional information from party manifestos; Garz et al. (2020) also employ a sentiment dictionary for German political language.

[40] The approach by Dewenter et al. (2016) is, for instance, based on tonality data from MediaTenor.

[41] Gentzkow et al. (2019) provide an overview of the opportunities and challenges of text as data.

bias, i.e., whether there is a selection or a distortion bias or both. Similarly, we cannot determine whether the bias is demand or supply driven. Second, the smaller the number of political parties and thereby of observations per news outlet, the smaller the number of values that the Spearman rank correlation coefficient between referral shares and the parties' position can take on. Even for two party democracies, however, our method can be used if reliable data on the political position of individual politicians are available. We further explore this option in Appendix C, where we utilize the ADA-Scores of Members of the US Congress. Third, our approach only works if the MPs who share news items are sufficiently representative of all MPs. Therefore, we caution against using our approach in countries where only few politicians are active on social media. Fourth, our approach is applicable only to online news outlets. Yet, since nowadays every major news outlet also operates online, we do not consider this as an important caveat. Relatedly, the measure cannot be applied to small news outlets whose news items are never shared by politicians. This does not, however, generally preclude the investigation of local news outlets. One could, for instance, study the sharing patterns of *local* politicians to determine the political position of *local* online news outlets, which would be an interesting direction for further research.

A. Tweet examples (translated from German into English)

A.1. Examples of non-criticizing tweets

Grüne tweeted:

> 12.000 plastic particles in one (!) litre arctic ice. We do not only poison the fish in the sea, but everything will end up in our bodies. Time to act. Stop #plasticpollution #plastictax. `http://www.tagesschau.de/ausland/mikroplastik-arktis-101.html`

SPD tweeted:

> Civil insurance: Well explained on Spiegel Online. `http://spon.de/ae7kR`

LINKE tweeted:

> It is good that @Simone_Lange opposes #Hartz4 so clearly. Otherwise very sad. @dieLinke is the social alternative and will continue to exert pressure for a fundamentally different policy. `http://m.spiegel.de/politik/deutschland/spd-andrea-nahles-holt-nur-66-prozent-warum-die-partei-nicht-erneuerbar-ist-a-1204209.html`

A.2. Examples of criticizing tweets

LINKE tweeted:

> I also accuse the SPD of playing a waiting game! But it is not correct that the LINKE supports the proposal by the FDP in its current form! #219a must be deleted. Induced abortion has no place in the penal code. `https://www.zeit.de/politik/deutschland/2018-03/werbeverbot-abtreibungen-linke-vorwurf-verzoegerung-ausschuss-groko`

AfD tweeted:

> While @PoggenburgAndre is politically "classified", @DLF of course abstains from doing so for the former secret police collaborator #Kahane. And you really wonder why fewer and fewer citizens trust your reporting? `https://www.deutschlandfunk.de/parlamentarische-anfragen-afd-will-demokratie-vereinen.862.de.html?dram:article_id=408111`

B. Sample of MPs

Our sample is limited to the selection of MPs who share news items on Twitter. This would be a concern if the political position of these MPs was systematically different from the political position of all MPs of their parties, as it may lead to different rankings of the relative number of Twitter referrals to the news outlets. Four arguments, however, speak against concerns about the nature of our sample.

First, the majority of MPs is active on Twitter. We find that our sample comprises 391 out of 707 MPs; 94 further MPs use Twitter, but do not refer to one of the news outlets under consideration during our observation period. Moreover, our results are not driven by a small number of excessive Twitter users. When we exclude the 10% most active MPs from each party from the analysis, the Spearman rank correlation coefficient remains nearly unchanged (Table 5, row 10).

Second, we study the effect of observable MP characteristics on the intensive and on the extensive margin of Twitter referrals. To this end, we obtain information on the MPs' age, gender, education, and political experience (in terms of election periods in the Bundestag) from `bundestag.de` and estimate

$$Y_i = \alpha_0 + \alpha_1 Age_i + \alpha_2 Female_i + \alpha_3 PhD_i + \alpha_4 Exp_i + \sum_{j=1}^{6} \beta_j Party_{ij} + \sum_{j=1}^{6} \gamma_j (Age_i * Party_{ij}) + \sum_{j=1}^{6} \delta_j (Female_i * Party_{ij}) + \varepsilon_i \quad (3)$$

by OLS. The dependent variable in equation (3) is either a dummy that indicates whether MP i eventually refers to one of the news outlets under consideration, or it corresponds to the absolute number of Twitter referrals of MP i. $Party_{ij}$, $j = 1, ..., 6$, is party dummy equal to one if MP i is affiliated to party j, with the most left-wing party LINKE as omitted category.

Columns 1 to 5 in Table 7 demonstrate that an MP's probability to eventually refer to one of the news outlets under consideration diminishes in age, but only slightly. According to our estimates, an additional year of age decreases the probability to eventually refer to a news outlet by about one percentage point; a standard deviation increase in age leads to a ten percentage point reduction, which corresponds to 20% of a standard deviation in the dependent variable. To put these numbers into perspective, note that the average MP is 52.5 years old, the average MP who shares news items on Twitter is 50.1, and the average MP who does not share news items is 55.5 years old.[42] Among those MPs who share news items, however, the older share more, and the average tweet in our data is written by an MP who is 51.5 years old.

The effect of political experience on the MPs' probability to eventually refer to a news

[42]The average MP who uses Twitter but does not refer to a news outlet during our observation period is 54.5 years old.

outlet disappears once we control for party affiliation; the effect of gender, in contrast, becomes statistically significant in Columns 2 and 3, but vanishes if we allow the effect to differ between parties in Columns 4 and 5. The results are similar when we use a logistic regression instead of a linear probability model.

Columns 6 to 10 in Table 7 show the relation between observable MP characteristics and the extensive margin of Twitter referrals among those politicians who refer at least once to the news outlets under consideration. The coefficients for gender, education, and political experience are statistically insignificant for all specifications. In contrast to Columns 1 to 5, the effect of age on the number of Twitter referrals is ambiguous: the coefficient is positive in Columns 6, 7, and 9, and negative in Columns 8 and 10; moreover, it is weakly statistically significant in Columns 6, 8, and 10. The effect size is small, though: an additional year of age corresponds to less than one referral more (or less); a one standard deviation increase in age leads to a six to nine units change in the number of referrals, which corresponds to less than 10% of a standard deviation in the dependent variable.

Third, because of these indications that age is related to sharing news items, we run an additional analysis where we weight each MP's Twitter referrals by her inverse probability to eventually refer to one of the news outlets under consideration.[43] MPs with a low probability to eventually refer to a news outlet are given large, and MPs with a high probability to eventually refer to a news outlet are given small weights (see, e.g., Wooldridge, 2007).

To this end, we obtain the MPs' predicted probabilities from equation (3), where we use the logit specification to ensure nonnegative probabilities, and the full set of controls. Row 11 of Table 5 shows that for the majority of news outlets, the Spearman rank correlation coefficients based on the weighted referral shares are identical to our main results. In particular, our main finding that *BILD* and *Welt* are positioned on the right, and *Zeit*, *Spiegel*, and *Deutschlandfunk* are positioned on the left of the political spectrum is unaffected.

As a fourth argument against concerns about the nature of our sample, we demonstrate that the political behavior of MPs who share news items on Twitter is similar to the political behavior of MPs who do not share news items. To this end, we obtain information on all roll-call votes during our observation period from `bundestag.de`.[44] Although German MPs often vote along the party lines (e.g., Sieberer, 2010), they are not obliged to do so – in fact, the enforcement of a strong party discipline is against the German Constitution.[45] Hence, the roll-call votes from the Bundestag allow us to check if the average political position of MPs who share news items on Twitter deviates from the average political position of MPs who do not share news items.

There were 22 roll-call votes during our observation period. MPs could vote "yes" or "no", explicitly abstain from voting, or not cast a vote at all, where we code "yes" as 1, "no" as -1, and the remaining outcomes as 0. Based on this coding, we compute the

[43] Cornesse et al. (2020) review inverse probability weighting for nonprobability samples.

[44] Roll-call votes are often used to put the political position of MPs on the public record (e.g., Sieberer et al., 2020).

[45] See Article 38, (1), Sentence 2.

average outcome for each of the 22 roll-cast vote for each party and for MPs who share news items on Twitter and for MPs who do not share news items. Then, we compute the average vote for MPs who share news items via Twitter and MPs who do not for each party. Columns 1 and 2 of Table 8 show the results. We find that, for each party, the difference in the average roll-call vote between MPs who share and who do not share news items via Twitter is small, which indicates that their political position is similar.

In addition to that, we use the roll-call votes to check whether MPs who share news items on Twitter are generally more likely to deviate from the party line than MPs who do not share news items. To this end, we determine how the majority of each party voted on each roll-call vote. Then, we check for each MP if he or she has voted along or against the party line. Columns 3 and 4 in Table 8 display the average shares of MPs who voted in accordance with their parties. In line with the evidence from Columns 1 and 2, we find that the conformity in voting behavior is large for all parties and, in particular, that the difference between MPs who share and who do not share news items on Twitter is negligible.

C. Evidence from the USA

As argued in Section 7, our approach can be used for two party democracies if reliable information on the political position of individual politicians is available. In this section, we further explore this option, using Twitter referrals and ADA Scores of Members of the 116th US Congress (elected January 2019 to January 2021).[46]

ADA Scores are computed by the *Americans for Democratic Action*, a liberal American political organization advocating progressive policies.[47] The ADA identifies key policy issues and tracks how Members of Congress vote on them. Each year, the organization selects the twenty roll-call votes that they consider as most important during that session. Each Member of Congress receives five points per vote if he or she voted in accordance with ADA, and zero points if he or she did not or was absent. Thus, the maximum ADA Score is 100 (considered as "liberal"), and the minimum ADA Score is 0 (considered as "conservative"). The ADA publishes its Scores on its website; the most recent available ADA Scores are computed for 2019.[48]

Following the approach from Sections 3 and 4, we proceed as follows. First, we obtain every tweet from every Member of the 116th US Congress who is active on Twitter and whose ADA Score is available from 14th June 2020 to 29th January 2021. Next, we check which tweets share news items published by a major US online news outlet. To determine which news outlets to consider, we retrieve the fifteen most visited news websites from Statista.[49] Excluding news aggregators and British websites from the analysis, nine major

[46]ADA Scores have formerly been employed, e.g., by Groseclose et al. (1999) and Groseclose and Milyo (2005).

[47]See https://adaction.org. Viewed: Feb 2021.

[48]See https://adaction.org/ada-voting-records/. Viewed: Feb 2021.

[49]See https://www.statista.com/statistics/381569/leading-news-and-media-sites-usa-by-

news outlets remain (see Table 9). Then, in contrast to our main analysis, we compute each Member's *individual* referral share to each of the nine news outlets. Finally, for each news outlet, we compute the *Neymann Pearson correlation coefficient* based on the individual referral shares and the individual ADA scores.[50]

Table 9 shows the results. Each correlation coefficient is based on $N = 426$ observations. In contrast to our main analysis, positive values correspond to left-leaning outlets and negative values correspond to right-leaning outlets, because a larger ADA Score refers to a more *left-leaning* politician.[51] Thus, we find that *CNN*, *NYTimes*, *NBC*, *Washington Post*, and the *LA Times* are positioned on the left, *Wall Street Journal* and *Fox News* are positioned on the right, and *ABC* and *USA Today* are positioned in the center of the political spectrum.

Our estimates are highly correlated with the results from Groseclose and Milyo (2005) and Gentzkow and Shapiro (2010). Gentzkow and Shapiro (2010) compute the political position of five news outlets whom we consider, too: *LA Times*, *NY Times*, *USA Today*, *Washington Post*, and *Wall Street Journal*.[52] The correlation between our Neymann Pearson correlation coefficient and the results from Gentzkow and Shapiro (2010) for these five news outlets is equal to 0.76. Groseclose and Milyo (2005) compute the political position of all outlets whom we consider; in some instances, they even provide two different measures for one outlet (e.g., "ABC Good Morning America" and "ABC World News Tonight") – we consider the average of their estimates in such cases. The correlation between our Neymann Pearson correlation coefficient and the results from Groseclose and Milyo (2005) is equal to 0.17; however, this result is driven by the *Wall Street Journal*.[53] When we exclude the *Wall Street Journal* from the analysis, the correlation between our coefficients and the results from Groseclose and Milyo (2005) is equal to 0.77.

For comparison, we also report what happens if we apply exactly the same methodology as on the German data. To this end, we aggregate the absolute number of Twitter referrals on the party level (Democratic and Republican) and compute the relative number of Twitter referrals by party and news outlet. Table 9 shows the corresponding referral shares. As there are only two political parties, the Spearman rank correlation coefficient between party positions and referral shares takes on only two values, +1 and -1, indicating whether the Democratic or Republican referral share is higher.

`share-of-visits/`. Viewed: Feb 2021.

[50]We find that 92% of the Members of the US Congress in our sample use Twitter and 86% refer at least once to one of the news outlets under consideration. The average ADA Score among all Democrats is equal to 87.8, the average ADA Score among Democrats who refer at least once to one of the news outlets under consideration is equal to 88.8. The average ADA Score among all Republicans is equal to 7.5 and among Republicans who refer at least once to one of the news outlets under consideration is equal to 7.7.

[51]In our main analysis, a higher rank refers to a more *right-leaning party*.

[52]We use the Slant Quotients as reported in Groseclose (2011) (Table 15.3 on p.175), an affine transformation of the original results in Gentzkow and Shapiro (2010).

[53]Groseclose and Milyo (2005) themselves note that their finding on the Wall Street is a surprise, and explain it by the fact that their estimate refers to the news section only, and not to editorial pages. See Groseclose (2011, p.176) for further discussion. Our data refer to both the news section and editorial pages.

References

Adamic, Lada A and Natalie Glance (2005) "The political blogosphere and the 2004 US election: divided they blog," in *Proceedings of the 3rd international workshop on Link discovery*, 36–43, ACM.

An, Jisun, Meeyoung Cha, Krishna Gummadi, Jon Crowcroft, and Daniele Quercia (2012) "Visualizing media bias through Twitter," in *Sixth International AAAI Conference on Weblogs and Social Media*.

An, Jisun, Daniele Quercia, and Jon Crowcroft (2014) "Partisan sharing: Facebook evidence and societal consequences," in *Proceedings of the second ACM conference on Online social networks*, 13–24, ACM.

Aruguete, Natalia and Ernesto Calvo (2018) "Time to# protest: Selective exposure, cascading activation, and framing in social media," *Journal of Communication*, **68** (3), 480–502.

Bakshy, Eytan, Solomon Messing, and Lada A Adamic (2015) "Exposure to ideologically diverse news and opinion on Facebook," *Science*, **348** (6239), 1130–1132.

Barberá, Pablo, John T Jost, Jonathan Nagler, Joshua A Tucker, and Richard Bonneau (2015) "Tweeting from left to right: Is online political communication more than an echo chamber?" *Psychological Science*, **26** (10), 1531–1542.

Bond, Robert, Christopher Fariss, Jason J. Jones, Adamd. I. Kramer, Cameron Marlow, Jaime E. Settle, and James H. Fowler (2012) "A 61-million-person experiment in social influence and political mobilization," *Nature*, **489** (7415), 295–298.

Boutet, Antoine, Hyoungshick Kim, and Eiko Yoneki (2012) "What's in your tweets? I know who you supported in the UK 2010 general election," in *Sixth International AAAI Conference on Weblogs and Social Media*.

Cohen, Jacob (1988) *Statistical power analysis for the behavioral sciences*: Academic press.

Colleoni, Elanor, Alessandro Rozza, and Adam Arvidsson (2014) "Echo chamber or public sphere? Predicting political orientation and measuring political homophily in Twitter using big data," *Journal of Communication*, **64** (2), 317–332.

Cornesse, Carina, Annelies G Blom, David Dutwin, Jon A Krosnick, Edith D De Leeuw, Stéphane Legleye, Josh Pasek, Darren Pennay, Benjamin Phillips, Joseph W Sakshaug et al. (2020) "A review of conceptual approaches and empirical evidence on probability and nonprobability sample survey research," *Journal of Survey Statistics and Methodology*, **8** (1), 4–36.

Dallmann, Alexander, Florian Lemmerich, Daniel Zoller, and Andreas Hotho (2015) "Media bias in german online newspapers," in *Proceedings of the 26th ACM Conference on Hypertext & Social Media*, 133–137, ACM.

DellaVigna, Stefano and Eliana La Ferrara (2016) "Economic and social impacts of the media," in *Handbook of Media Economics*, **1**: Elsevier, 723–768.

Dewenter, Ralf, Uwe Dulleck, and Tobias Thomas (2016) *Does the 4th estate deliver? Towards a more direct measure of political media bias*: DICE Discussion Paper.

infratest dimap, Berlin (2015) "AfD rückt nach rechts, CDU nach links. Die Positionierung der politischen Parteien im Links-Rechts-Kontinuum."

Forschungsgruppe Wahlen, Mannheim (2017) "Politbarometer 2016 (Kumulierter Datensatz)," GESIS Datenarchiv, Köln. ZA6888 Datenfile Version 1.0.0 (2017), doi:10.4232/1.12824.

Garrett, R Kelly (2009a) "Echo chambers online?: Politically motivated selective exposure among Internet news users," *Journal of Computer-Mediated Communication*, **14** (2), 265–285.

——— (2009b) "Politically motivated reinforcement seeking: Reframing the selective exposure debate," *Journal of Communication*, **59** (4), 676–699.

Garz, Marcel, Jil Sörensen, and Daniel F Stone (2020) "Partisan selective engagement: Evidence from Facebook," *Journal of Economic Behavior & Organization*, **177**, 91–108.

Gentzkow, Matthew, Bryan Kelly, and Matt Taddy (2019) "Text as data," *Journal of Economic Literature*, **57** (3), 535–74.

Gentzkow, Matthew and Jesse M Shapiro (2010) "What drives media slant? Evidence from US daily newspapers," *Econometrica*, **78** (1), 35–71.

Gentzkow, Matthew, Jesse Shapiro, and Daniel Stone (2016) "Media bias in the marketplace: Theory," in *Handbook of Media Economics*, **1**: Elsevier, 623–645.

Groeling, Tim (2013) "Media bias by the numbers: Challenges and opportunities in the empirical study of partisan news," *Annual Review of Political Science*, **16**, 129–151.

Groseclose, Tim (2011) *Left turn: How liberal media bias distorts the American mind*: St. Martin's Press.

Groseclose, Tim, Steven D Levitt, and James M Snyder Jr (1999) "Comparing interest group scores across time and chambers: Adjusted ADA scores for the US Congress," *American Political Science Review*, 33–50.

Groseclose, Tim and Jeffrey Milyo (2005) "A measure of media bias," *The Quarterly Journal of Economics*, **120** (4), 1191–1237.

Hermida, Alfred, Seth C Lewis, and Rodrigo Zamith (2014) "Sourcing the Arab Spring: A case study of Andy Carvin's sources on Twitter during the Tunisian and Egyptian revolutions," *Journal of Computer-Mediated Communication*, **19** (3), 479–499.

Ho, Daniel E and Kevin M Quinn (2008) "Measuring explicit political positions of media," *Quarterly Journal of Political Science*, **3** (4), 353–377.

Jungherr, Andreas (2014) "The logic of political coverage on Twitter: Temporal dynamics and content," *Journal of Communication*, **64** (2), 239–259.

——— (2016) "Twitter use in election campaigns: A systematic literature review," *Journal of Information Technology & Politics*, **13** (1), 72–91.

Knobloch-Westerwick, Silvia and Jingbo Meng (2009) "Looking the other way: Selective exposure to attitude-consistent and counterattitudinal political information," *Communication Research*, **36** (3), 426–448.

——— (2011) "Reinforcement of the political self through selective exposure to political messages," *Journal of Communication*, **61** (2), 349–368.

Laver, Michael (2014) "Measuring policy positions in political space," *Annual Review of Political Science*, **17**, 207–223.

Luca, Michael (2016) "User-generated content and social media," in *Handbook of Media Economics*, **1**: Elsevier, 563–592.

Owen, Donald B (1962) *Handbook of statistical tables*: Addison-Wesley Publication Company.

Puglisi, Riccardo and James Snyder (2016) "Empirical Studies of Media Bias," in *Handbook of Media Economics*, **1**: Elsevier, 647–667.

Shin, Jieun and Kjerstin Thorson (2017) "Partisan selective sharing: The biased diffusion of fact-checking messages on social media," *Journal of Communication*, **67** (2), 233–255.

Sieberer, Ulrich (2010) "Behavioral consequences of mixed electoral systems: Deviating voting behavior of district and list MPs in the German Bundestag," *Electoral Studies*, **29** (3), 484–496.

Sieberer, Ulrich, Thomas Saalfeld, Tamaki Ohmura, Henning Bergmann, and Stefanie Bailer (2020) "Roll-call votes in the german bundestag: A new dataset, 1949–2013," *British Journal of Political Science*, **50** (3), 1137–1145.

Siegel, Sidney and NJ Castellan (1988) "Nonparametric statistics for the behavioral sciences," *Nonparametric Statistics for the Behavioral Sciences, McGraw-Hill, New York*, 190–222.

Wooldridge, Jeffrey M (2007) "Inverse probability weighted estimation for general missing data problems," *Journal of Econometrics*, **141** (2), 1281–1301.

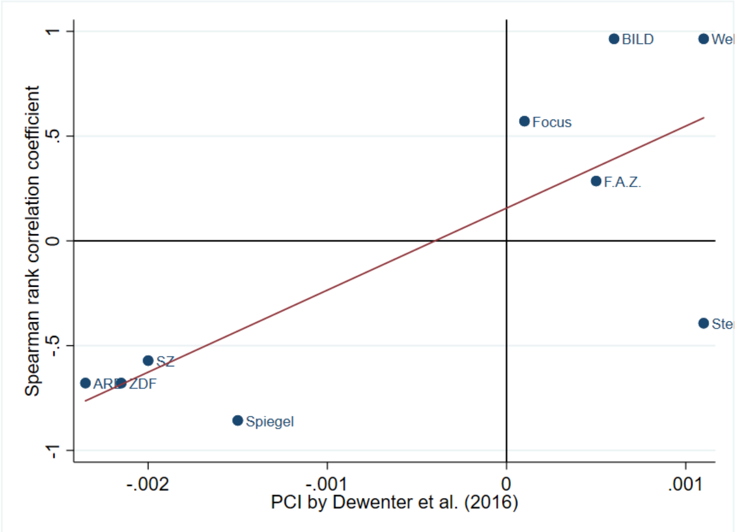

Figure 1: Comparison of the Spearman rank order coefficient to the weighted PCI by Dewenter et al. (2016).

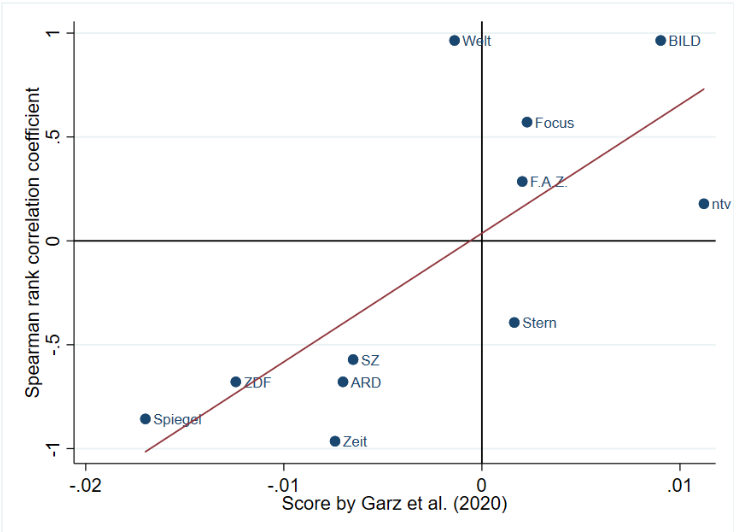

Figure 2: Comparison of the Spearman rank order coefficient to the score by Garz et al. (2020).

Table 1: Absolute number of Twitter referrals by party

	BILD	Spiegel	Focus	n-tv	Welt	Zeit	SZ	Stern	F.A.Z.	ARD	ZDF	D.funk	Total
LINKE	16	551	67	79	200	275	264	65	113	314	92	125	2,161
Grüne	99	896	63	64	430	425	619	32	382	349	94	217	3,670
SPD	73	749	58	51	324	290	347	48	237	188	78	133	2,576
FDP	123	293	102	85	542	128	117	23	375	88	37	66	1,979
CDU	280	283	130	89	707	145	193	28	484	256	69	140	2,804
CSU	17	22	4	3	54	6	23	0	25	9	5	7	175
AfD	674	564	912	286	2,175	255	202	86	572	363	81	95	6,265
Total	1,282	3,358	1,336	657	4,432	1,524	1,765	282	2,188	1,567	456	783	19,630

Notes: Table 1 shows the absolute number of Twitter referrals by party to each news outlet under consideration. Newspapers and magazines: *BILD* refers to news items from `bild.de`. *Spiegel* refers to news items from `spiegel.de`. *Focus* refers to news items from `focus.de`. *Welt* refers to news items from `welt.de`. *Zeit* refers to news items from `zeit.de`. *SZ* refers to news items from `sueddeutsche.de`. *Stern* refers to news items from `stern.de`. *F.A.Z.* refers to news items from `faz.net`. Public service broadcasters (television): *ARD* refers to news items from `tagesschau.de`. *ZDF* refers to news items from `zdf.de/nachrichten`. Public service broadcasters (radio): *D.funk* refers to news items from `deutschlandfunk.de`. Other online news outlets: *n-tv* refers to news items from `n-tv.de`.

Table 2: Relative number of Twitter referrals by party

	BILD	Spiegel	Focus	n-tv	Welt	Zeit	SZ	Stern	F.A.Z.	ARD	ZDF	D.funk	Total
LINKE	.0074	.2550	.0310	.0366	.0925	.1273	.1222	.0301	.0523	.1453	.0426	.0578	1
Grüne	.0270	.2441	.0172	.0174	.1172	.1158	.1687	.0087	.1041	.0951	.0256	.0591	1
SPD	.0283	.2908	.0225	.0198	.1258	.1126	.1347	.0186	.0920	.0730	.0303	.0516	1
FDP	.0622	.1481	.0515	.0430	.2739	.0647	.0591	.0116	.1895	.0445	.0187	.0334	1
CDU	.0999	.1009	.0464	.0317	.2521	.0517	.0688	.01	.1726	.0913	.0246	.0499	1
CSU	.0971	.1257	.0229	.0171	.3086	.0343	.1314	.0	.1429	.0514	.0286	.04	1
AfD	.1076	.0900	.1456	.0457	.3472	.0407	.0322	.0137	.0913	.0579	.0129	.0152	1

Notes: Table 2 shows the relative number of Twitter referrals by party to each news outlet under consideration. The relative numbers are computed based on the absolute numbers in Table 1. Newspapers and magazines: *BILD* refers to news items from `bild.de`. *Spiegel* refers to news items from `spiegel.de`. *Focus* refers to news items from `focus.de`. *Welt* refers to news items from `welt.de`. *Zeit* refers to news items from `zeit.de`. *SZ* refers to news items from `sueddeutsche.de`. *Stern* refers to news items from `stern.de`. *F.A.Z.* refers to news items from `faz.net`. Public service broadcasters (television): *ARD* refers to news items from `tagesschau.de`. *ZDF* refers to news items from `zdf.de/nachrichten`. Public service broadcasters (radio): *D.funk* refers to news items from `deutschlandfunk.de`. Other online news outlets: *n-tv* refers to news items from `n-tv.de`.

Table 3: Overview of the ranks

	Party	BILD	Spiegel	Focus	n-tv	Welt	Zeit	SZ	Stern	F.A.Z.	ARD	ZDF	D.funk
LINKE	1	1	6	4	5	1	7	4	7	1	7	7	6
Grüne	2	2	5	1	2	2	6	7	2	4	6	4	7
SPD	3	3	7	2	3	3	5	6	6	3	4	6	5
FDP	4	4	4	6	6	5	4	2	4	7	1	2	2
CDU	5	6	2	5	4	4	3	3	3	6	5	3	4
CSU	6	5	3	3	1	6	1	5	1	5	2	5	3
AfD	7	7	1	7	7	7	2	1	5	2	3	1	1

Notes: Table 3 shows the ranks (i) for the parties' political position from most left-wing to most right-wing and (ii) for the parties' relative number of Twitter referrals to the twelve news outlets. The ranks of the referral shares are computed based on Table 2. Newspapers and magazines: *BILD* refers to news items from `bild.de`. *Spiegel* refers to news items from `spiegel.de`. *Focus* refers to news items from `focus.de`. *Welt* refers to news items from `welt.de`. *Zeit* refers to news items from `zeit.de`. *SZ* refers to news items from `sueddeutsche.de`. *Stern* refers to news items from `stern.de`. *F.A.Z.* refers to news items from `faz.net`. Public service broadcasters (television): *ARD* refers to news items from `tagesschau.de`. *ZDF* refers to news items from `zdf.de/nachrichten`. Public service broadcasters (radio): *D.funk* refers to news items from `deutschlandfunk.de`. Other online news outlets: *n-tv* refers to news items from `n-tv.de`.

Table 4: Main results

	BILD	Spiegel	Focus	n-tv	Welt	Zeit	SZ	Stern	F.A.Z.	ARD	ZDF	D.funk
Pooled												
ρ_o	0.964***	-0.857**	0.571	0.179	0.964***	-0.964***	-0.571	-0.393	0.286	-0.679	-0.679	-0.857**
p-value	(0.0028)	(0.024)	(0.200)	(0.714)	(0.0028)	(0.0028)	(0.200)	(0.396)	(0.556)	(0.110)	(0.110)	(0.024)
Politics												
ρ_o	0.750*	-0.857**	0.393	-0.071	0.964***	-0.857**	-0.750*	-0.714*	0.357	-0.750*	n.a.	n.a.
p-value	(0.066)	(0.024)	(0.396)	(0.906)	(0.003)	(0.0238)	(0.066)	(0.088)	(0.444)	(0.066)		
Business												
ρ_o	0.893**	-0.857**	-0.143	0.321	0.857**	-0.321	-0.750*	n.a.	0.750*	-0.893**	n.a.	n.a.
p-value	(0.012)	(0.024)	(0.782)	(0.498)	(0.024)	(0.498)	(0.066)		(0.066)	(0.012)		
Other												
ρ_o	0.464	-0.857**	0.929***	0.214	0.750*	-0.714*	-0.179	0.321	0.536	n.a.	n.a.	n.a.
p-value	(0.302)	(0.024)	(0.007)	(0.661)	(0.066)	(0.088)	(0.713)	(0.498)	(0.235)			

Notes: Table 4 shows the Spearman rank correlation coefficient computed for each news outlet under consideration. *Pooled* corresponds to the results that we obtain from using all Twitter referrals, as presented in Section 5.1. *Politics*, *Business*, and *Other* show the Spearman rank correlation coefficient by newspaper section, where *Other* corresponds to feuilleton, sports, and knowledge, as presented in Section 5.2. Newspapers and magazines: *BILD* refers to news items from `bild.de`. *Spiegel* refers to news items from `spiegel.de`. *Focus* refers to news items from `focus.de`. *Welt* refers to news items from `welt.de`. *Zeit* refers to news items from `zeit.de`. *SZ* refers to news items from `sueddeutsche.de`. *Stern* refers to news items from `stern.de`. *F.A.Z.* refers to news items from `faz.net`. Public service broadcasters (television): *ARD* refers to news items from `tagesschau.de`. *ZDF* refers to news items from `zdf.de/nachrichten`. Public service broadcasters (radio): *D.funk* refers to news items from `deutschlandfunk.de`. Other online news outlets: *n-tv* refers to news items from `n-tv.de`. Exact p-values in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Robustness Checks

Row no.	Robustness check	BILD	Spiegel	Focus	n-tv	Welt	Zeit	SZ	Stern	F.A.Z.	ARD	ZDF	D.funk	taz
(1)	No criticizing tweets	0.929***	-0.857**	0.750*	0.179	0.964***	-1.000***	-0.464	-0.500	0.429	-0.750*	-0.464	-0.857**	
	p-value	(0.0068)	(0.024)	(0.066)	(0.714)	(0.0028)	(0.0004)	(0.302)	(0.266)	(0.354)	(0.066)	(0.302)	(0.024)	
(2)	Exclude LINKE	0.943**	-0.886**	0.771	0.371	0.943**	-0.943**	-0.771	-0.029	-0.143	-0.486	-0.486	-0.829*	
	p-value	(0.0166)	(0.034)	(0.102)	(0.498)	(0.0166)	(0.0166)	(0.102)	(1.000)	(0.802)	(0.356)	(0.356)	(0.058)	
(3)	Exclude AfD	0.943**	-0.771	0.314	-0.314	0.943**	-1.000***	-0.314	-0.657	0.714	-0.714	-0.486	-0.771	
	p-value	(0.0166)	(0.102)	(0.564)	(0.564)	(0.0166)	(0.0028)	(0.564)	(0.176)	(0.136)	(0.136)	(0.356)	(0.102)	
(4)	Exclude LINKE and AfD	0.900*	-0.800	0.600	-0.100	0.900*	-1.000**	-0.600	-0.400	0.500	-0.500	-0.100	-0.700	
	p-value	(0.084)	(0.134)	(0.350)	(0.950)	(0.084)	(0.0166)	(0.350)	(0.516)	(0.450)	(0.450)	(0.950)	(0.234)	
(5)	Include *taz*	0.964***	-0.857**	0.571	0.321	0.964***	-0.929***	-0.464	-0.393	0.429	-0.571	-0.571	-0.857**	-0.929***
	p-value	(0.0028)	(0.024)	(0.200)	(0.498)	(0.0028)	(0.0068)	(0.302)	(0.355)	(0.556)	(0.200)	(0.200)	(0.024)	(0.0068)
(6)	Absolute no. of tweets	0.607	-0.464	0.321	0.321	0.429	-0.643	-0.643	-0.179	0.357	-0.107	-0.571	-0.500	
	p-value	(0.166)	(0.302)	(0.498)	(0.498)	(0.354)	(0.138)	(0.138)	(0.714)	(0.444)	(0.840)	(0.200)	(0.266)	
(7)	Longitudinal analysis	0.964***	-0.857**	0.857**	0.643	0.857**	-0.857**	-0.750*	-0.393	0.464	-0.786**	-0.750*	-0.679	
	p-value	(0.0028)	(0.024)	(0.024)	(0.139)	(0.024)	(0.024)	(0.066)	(0.396)	(0.302)	(0.048)	(0.066)	(0.110)	
(8)	European Parliament	0.929***	-0.643	0.143	0.071	0.893**	-0.929**	-0.857**	0.252	0.643	-0.893**	-0.286	-0.143	
	p-value	(0.007)	(0.139)	(0.783)	(0.840)	(0.012)	(0.007)	(0.024)	(0.595)	(0.139)	(0.012)	(0.556)	(0.783)	
(9)	State Parliaments	1.000***	-0.786**	0.893**	0.714*	0.893**	-0.821**	-0.571	0.607	0.643	-0.857**	-0.893**	0.607	
	p-value	(0.0004)	(0.048)	(0.012)	(0.088)	(0.012)	(0.034)	(0.200)	(0.167)	(0.139)	(0.024)	(0.012)	(0.167)	
(10)	Exclude 10% most active MPs	0.857**	-0.857**	0.357	0.429	1.000***	-0.786*	-0.857**	-0.536	0.607	-0.750*	-0.679	-0.714*	
	p-value	(0.024)	(0.024)	(0.444)	(0.354)	(0.0004)	(0.048)	(0.024)	(0.238)	(0.167)	(0.066)	(0.110)	(0.088)	
(11)	Inverse prob. weighting	1.000***	-0.857**	0.464	0.321	0.964***	-0.964***	-0.750*	-0.393	0.286	-0.679	-0.679	-0.786**	
	p-value	(0.0004)	(0.024)	(0.302)	(0.498)	(0.0028)	(0.0028)	(0.066)	(0.396)	(0.556)	(0.110)	(0.110)	(0.048)	

Notes: The first row of Table 5 shows the Spearman rank correlation coefficient computed based on a randomly drawn subsample of tweets, excluding all tweets that were classified as criticizing (Section 6.1). The second, third, and forth rows show the Spearman rank correlation coefficient computed when excluding the tweets by LINKE, AfD, and both at the same time, respectively (Section 6.2.). The fifth row shows the Spearman rank correlation coefficients when *taz* is considered (Section 6.3.). The sixth row shows the Spearman rank correlation coefficient based on the *absolute* number of Twitter referrals as given in Table 1 (Section 6.3.). The seventh row shows the Spearman rank correlation coefficient based on tweets from Dec 2018 to July 2019 (Section 6.4.). The eighth row shows the Spearman rank correlation coefficient based on tweets from German Members of the European Parliament on tweets from Dec 2018 to July 2019 (Section 6.5.). The ninth row shows the Spearman rank correlation coefficient based on tweets from German Members of the German State Parliaments from Dec 2018 to July 2019 (Section 6.5.). The tenth row shows the Spearman rank correlation coefficient excluding the tweets from the 10% most active MPs from each party (Appendix B). The eleventh row shows the Spearman rank correlation coefficient based on weighted referrals (Appendix B). Newspapers and magazines: *BILD* refers to news items from `bild.de`. *Spiegel* refers to news items from `spiegel.de`. *Focus* refers to news items from `focus.de`. *Welt* refers to news items from `welt.de`. *Zeit* refers to news items from `zeit.de`. *SZ* refers to news items from `sueddeutsche.de`. *Stern* refers to news items from `stern.de`. *F.A.Z.* refers to news items from `faz.net`. *taz* refers to news items from `taz.de`. Public service broadcasters (television): *ARD* refers to news items from `tagesschau.de`. *ZDF* refers to news items from `zdf.de/nachrichten`. Public service broadcasters (radio): *D.funk* refers to news items from `deutschlandfunk.de`. Other online news outlets: *n-tv* refers to news items from `n-tv.de`. Exact *p*-values in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Correlation matrix Spearman coefficients

	NP 2017/18	NP 2018/19	EP 2018/19	SP 2018/19
NP 2017/18	1.0000			
NP 2018/19	0.9720	1.0000		
EP 2018/19	0.8664	0.8517	1.0000	
SP 2018/19	0.8235	0.8897	0.8184	1.0000

Notes: Correlation matrix for the Spearman rank correlation coefficients based on different sets of Twitter referrals to online news outlets. *NP 2017/18* corresponds to the Spearman rank correlation coefficient computed based on Twitter referrals from German Members of (National) Parliament in the time period Oct 2017 to May 2018. *NP 2018/19* corresponds to the Spearman rank correlation coefficient computed based on Twitter referrals from German Members of (National) Parliament in the time period Dec 2018 to July 2019. *EP 2018/19* corresponds to the Spearman rank correlation coefficient computed based on Twitter referrals from German Members of European Parliament in the time period Dec 2018 to July 2019. *SP 2018/19* corresponds to the Spearman rank correlation coefficient computed based on tweets from Members of the German State Parliaments in the time period Dec 2018 to July 2019.

Table 7: Effect of observable MP characteristics

	(1) DTweet	(2) DTweet	(3) DTweet	(4) DTweet	(5) DTweet	(6) Tweets	(7) Tweets	(8) Tweets	(9) Tweets	(10) Tweets
Age	-0.0116***	-0.0125***	-0.00965**	-0.0126***	-0.0100**	1.000*	0.677	-0.811*	0.687	-0.826*
	(0.00184)	(0.00181)	(0.00474)	(0.00182)	(0.00480)	(0.528)	(0.465)	(0.434)	(0.453)	(0.427)
Female	0.00589	-0.0806**	-0.0797**	0.00135	-0.00346	-3.681	-0.129	1.080	9.161	10.99
	(0.0396)	(0.0383)	(0.0384)	(0.104)	(0.104)	(8.673)	(7.767)	(7.494)	(10.81)	(9.805)
PhD	0.0476	0.0527	0.0588	0.0521	0.0574	-6.057	-2.867	-0.531	-2.962	-0.883
	(0.0463)	(0.0445)	(0.0449)	(0.0446)	(0.0451)	(10.91)	(10.83)	(11.41)	(10.96)	(11.54)
Experience	-0.0233**	0.00224	0.00343	0.00315	0.00467	-5.149	1.905	3.403	1.725	3.111
	(0.0107)	(0.0115)	(0.0121)	(0.0115)	(0.0121)	(3.146)	(2.270)	(2.175)	(2.272)	(2.223)
AfD		-0.0809	0.249	-0.0581	0.225		63.96***	-135.8*	68.53***	-136.2*
		(0.0728)	(0.311)	(0.0897)	(0.319)		(20.78)	(79.10)	(24.09)	(77.42)
CDU		-0.395***	0.0581	-0.352***	0.0791		-0.632	-32.41	7.978	-27.96
		(0.0620)	(0.304)	(0.0812)	(0.307)		(10.99)	(36.56)	(13.15)	(37.16)
CSU		-0.491***	-0.469	-0.441***	-0.406		-27.12***	-37.38	-24.56***	-37.17
		(0.0855)	(0.445)	(0.104)	(0.458)		(8.324)	(31.55)	(9.252)	(35.06)
FDP		-0.224***	-0.345	-0.179*	-0.323		6.202	3.271	9.861	7.411
		(0.0771)	(0.354)	(0.0965)	(0.360)		(13.47)	(54.46)	(15.73)	(61.08)
SPD		-0.182***	-0.0651	-0.0960	-0.00798		-10.67	-81.99**	-7.345	-79.30**
		(0.0651)	(0.341)	(0.0877)	(0.342)		(7.951)	(35.78)	(9.037)	(37.73)
GRUENE		0.129**	-0.145	0.0697	-0.163		24.77**	-91.04*	27.02*	-87.96
		(0.0645)	(0.327)	(0.0976)	(0.326)		(10.65)	(54.16)	(16.27)	(56.84)
AfD*Age			-0.00614		-0.00528			3.974**		4.043**
			(0.00594)		(0.00602)			(1.819)		(1.792)
CDU*Age			-0.00849		-0.00817			0.567		0.655
			(0.00576)		(0.00584)			(0.739)		(0.739)
CSU*Age			-0.000342		-0.000698			0.0836		0.174
			(0.00847)		(0.00858)			(0.627)		(0.658)
FDP*Age			0.00275		0.00308			-0.0207		-0.0111
			(0.00702)		(0.00708)			(0.963)		(1.020)
SPD*Age			-0.00223		-0.00173			1.383*		1.405*
			(0.00651)		(0.00655)			(0.760)		(0.744)
GRUENE*Age			0.00561		0.00492			2.270**		2.287**
			(0.00659)		(0.00655)			(1.127)		(1.086)
AfD*Female				0.0821	0.0742				-12.85	-0.975
				(0.155)	(0.154)				(42.24)	(39.06)
CDU*Female				-0.105	-0.0894				-39.01**	-38.92**
				(0.129)	(0.129)				(16.40)	(15.72)
CSU*Female				-0.153	-0.135				4.864	-7.635
				(0.198)	(0.200)				(15.44)	(14.78)
FDP*Female				-0.103	-0.0832				-6.817	-11.62
				(0.169)	(0.168)				(31.35)	(33.14)
SPD*Female				-0.195	-0.191				-6.019	-7.314
				(0.131)	(0.132)				(17.07)	(16.34)
GRUENE*Female				0.0916	0.0793				-5.605	-8.656
				(0.131)	(0.131)				(21.44)	(20.29)
Constant	1.208***	1.424***	1.270***	1.388***	1.251***	14.06	1.472	73.46***	-2.967	70.39***
	(0.0924)	(0.101)	(0.242)	(0.111)	(0.246)	(19.60)	(21.84)	(22.67)	(21.68)	(23.35)
N	707	707	707	707	707	391	391	391	391	391
R^2	0.076	0.194	0.203	0.202	0.210	0.014	0.082	0.105	0.085	0.107

Notes: Robust standard errors in parentheses. The dependent variable in Columns 1 to 5 is a dummy variable that indicates if MP i eventually shares a news items on Twitter. The dependent variable in Columns 6 to 10 is equal to the absolute number of Twitter referrals to the news outlets under consideration during our observation period. *Age* corresponds to the age of MP i in years, *Female* and *PhD* are dummies that are equal to 1 if MP i is female or has a PhD, respectively. *Experience* corresponds to MP i's number of election periods in the Bundestag. *AfD*, *CDU*, *CSU*, *FDP*, *SPD*, and *GRUENE* are party indicators with LINKE as the omitted category. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Evidence from roll-call votes

	Average votes		Vote as party majorities	
	Tweeting MPs	Non-Tweeting MPs	Tweeting MPs	Non-Tweeting MPs
AfD	-0.235	-0.241	0.91	0.91
CSU	0.679	0.673	0.95	0.94
CDU	0.665	0.673	0.93	0.94
FDP	0.553	0.545	0.93	0.93
SPD	0.597	0.620	0.89	0.89
GRUENE	0.124	0.174	0.84	0.86
LINKE	-0.630	-0.646	0.84	0.88

Notes: Table 8 presents evidence on the behavior of tweeting and non-tweeting MPs in roll-coll votes. Columns 1 and 2 show the average vote of tweeting and non-tweeting MPs in the 22 roll-coll votes during our observation period by Party. Columns 3 and 4 show the average share of MPs who voted along their party line in the 22 roll-call votes during our observation period for of tweeting and non-tweeting MPs by Party.

Table 9: Evidence from the USA

	CNN	NYTimes	NBC	WPost	WSJ	ABC	USAToday	LATimes	FoxNews
Neymann Pearson	0.416***	0.626***	0.294***	0.220***	-0.475***	0.055	-0.012	0.110**	-0.549***
p-value	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.257)	(0.808)	(0.023)	(0.000)
Referral share Dem.	0.161	0.308	0.101	0.260	0.037	0.040	0.033	0.031	0.030
Referral share Rep.	0.057	0.099	0.028	0.225	0.227	0.029	0.040	0.011	0.282

Notes: Table 9 presents evidence from the US Congress. The top row shows the Neymann Pearson correlation coefficient based on the individual ADA Scores of $N = 426$ politicians and their individual referral shares to the nine online news outlets under consideration. Higher values indicate that a news outlet is more left-leaning. The bottom rows show the referral shares aggregated on party level, where *Referral share Dem.* corresponds to the Democrats and *Referral share Rep.* corresponds to the Republicans. Outlets: *CNN* refers to news items from `cnn.com`. *NYTimes* refers to news items from `nytimes.com`. *NBC* refers to news items from `nbcnews.com`. *WPost* refers to news items from `washingtonpost.com`. *WSJ* refers to news items from `wsj.com`. *ABC* refers to news items from `abc.com`. *USAToday* refers to news items from `usatoday.com`. *LATimes* refers to news items from `latimes.com`. *FoxNews* refers to news items from `foxnews.com`.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.