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ARTICLE

The Left-liberal Skew of Western Media

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ABSTRACT

We gathered survey data on journalists' political views in 17 Western countries. We then matched these data to outcomes from national elections, and constructed metrics of journalists' relative preference for different political parties. Compared to the general population of voters, journalists prefer parties that have more left-wing positions overall (r's -.47 to -.53, depending on the metric used), and that are associated with certain ideologies, namely environmentalism, feminism, social liberalism, socialism, and support for the European Union. We used Bayesian model averaging to assess the validity of the predictors in multivariate models. We found that, of the ideology tags in our dataset, 'conservative' (negative), 'nationalist' (negative) and 'green' (positive) were the most consistent predictors with nontrivial effect sizes. We also computed estimates of the skew of journalists' political views in different countries. Overall, our results indicate that the Western media has a left-liberal skew.

1. Introduction

It is widely claimed that the media leans left or is biased against non-left-wing views [1-4]. However, such claims have been disputed by others [5,6]. One significant limitation of the empirical literature on media bias is that it is narrowly focused on the United States [7], a problem with quantitative media research generally [8]. Hence we attempted to quantify the political skew of the Western media as a whole.

How can one study political bias in the media? We are aware of three main approaches. First, one can analyze who owns or funds the media. This approach is based on the assumption that owners exert some kind of influence over the outlets they own. Interestingly, both far-left and far-right commentators have cited analyses of media owners in support of their views. Far-left commentators have highlighted that the media are owned almost entirely by the wealthy, who tend to hold conservative views on economic issues [9]. Hence if owners do influence the outlets they own, it would tend to be in the direction of maintaining the status quo, which is assumed to benefit them. On the far right, commentators have taken a similar approach, except that instead of emphasising owners' wealth, they have focussed on their ethnicity. In particular, it has been claimed that Jewish-owned media tend to support specific interests such as defending Israel, or trying to undermine nationalism in Western countries [10,11].

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A second approach to studying media bias is to analyze the content of the media itself [12,13]. Traditionally, this involved reading through media output, and then manually coding it as supporting one ideology or another. Because this method relies on the subjective judgment of coders [9], it is open to the criticism that those coders themselves might be biased, or that there are second-order effects whereby sources seem right-wing while being neutral, due to most other media being left-wing [7]. In addition to these criticisms, manual coding is extremely labor intensive and is therefore difficult to implement in practice. To get around these issues, studies have increasingly relied on machine learning analysis of media content [14].

One study ranked media outlets from liberal to conservative by comparing the number of times they cited various think tanks or policy groups to the number of times those groups were cited by Democrat versus Republican members of the US Congress. Media outlets that tended to cite groups more often cited by Democrats were classified as more liberal, whereas those that tended to cite groups more often cited by Republicans were classified as more conservative [15]. In a related study, Gentzkow and Shapiro (2010) [16] trained algorithms to identify the phrases that most differentiated Democrat versus Republican members of Congress, and then classified newspapers based on how frequently they used the phrases that were typical of Democrats versus Republicans. Their rank ordering of major US news outlets was similar to the one obtained by Groseclose and Milyo (2005) [15], and they found that most news outlets had a left-wing tilt. (Interestingly, they also found that ownership of media outlets was of comparatively minor importance).

Another way to utilise machine learning is to train algorithms to code media content based on text cues which may be incomprehensible to humans but that do show predictive validity [17]. This necessitates having a text corpus with known (or assumed) political leanings, which can be obtained either by recruiting humans to evaluate a subset of the data, or by relying on sources with known (or assumed) positions, such as politicians who have given speeches. For example, Budak et al. (2016) [17] used human judges to rate a subset of their data, and then evaluated the remaining, very large dataset using complex, trained models. Their method yielded a similar ranking of US news outlets to those that have been reported in previous studies.

A third approach to studying media bias is to analyse data on media personnel themselves [18]. Media organizations employ a variety of workers, the most important of whom are journalists and editors, with journalists comprising the lion's share of the workforce. As a matter of fact, our initial analysis of surveys of media personnel indicated that journalists constitute the vast majority of respondents to such surveys. As a consequence, any survey-based approach would have to focus on journalists, while analysing data on, say, editors only if it happened to be reported.

We took the approach of analysing media personnel themselves because we found that it was relatively easy to track down surveys from a variety of countries, including many that had received little previous attention, especially in the English language literature (e.g. Polish and Scandinavian surveys). Note that it would be much more difficult to analyse data from many countries using content analysis because the relevant models do not easily generalize across languages. Hence our approach can be considered particularly useful in this regard. We decided to focus our attention solely on Western countries because language barriers would have been prohibitive for non-Western countries.

A number of previous cross-national surveys of journalists have been carried out. Yet these did not generally include questions about voting behavior (or vote intentions), but only self-placement on a left-right scale. We consider this unsatisfactory in the present context because of the reference group effect, namely that journalists might rate themselves in comparison to others within their profession and extended network, rather than with respect to the general population. Furthermore, previous research has shown that self-placement is only moderately correlated with more complex measures of political views, such as factors derived from many multiple-choice questions [19-21]. To avoid this issue, we decided to collect data on journalists' voting behaviour or vote intentions.

1.1 How Media Bias Works: The Distortion Model

Before proceeding to the methods section, it is worth outlining the main causal model for the relationship between journalists' political views and media bias, which we consider to be the distortion model [7]. The model can be divided into three parts, which we will discuss in turn. First, survey evidence indicates that journalists have considerable leeway as to which stories they write and how they write them. By and large, journalists seek out stories in the information stream that surrounds them, which happens to include a lot of other journalists. Here political leanings are relevant, given that journalists are presumably more interested in stories that cast a favourable light on persons, parties or organizations with which they identify, as well as stories that cast a negative

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light on persons, parties or organisations to which they are opposed. This kind of bias has been termed *gatekeeping* or *selectivity* in the previous literature [22]. Although note that a recent US study found no evidence of a liberal bias in which news stories political journalists choose to cover [6] [1].

Second, journalists have many options concerning which sources to seek out when writing a story. Suppose a local university has just rolled out a new policy. If a particular journalist happens to support the new policy, he can choose to seek out only or predominantly sources that are likely to speak in its favor. Because there are always many relevant sources that could be sought out, some kind of selection has to be made. And one would expect this selection to produce a list of sources that comports with the journalist's own preferences. On some occasions, journalists may seek out particularly ill-informed members of the opposing side of the story, so as to make that side "look bad". When writing a story about the local university's new policy, the journalist could seek out a well-spoken professor who supports it, and a dissenting individual who is known to make particularly incoherent arguments.

Third, journalists have to make decisions about which words or images to use when writing a story [23]. How should a given individual be introduced or labeled? Consider Charles Murray, the author of the controversial book *The Bell Curve,* which is about intelligence and social inequality in the United States. Should he be described as 'far-right', 'controversial', or a 'pseudoscientist'? These are certainly labels that have been used for him. Or maybe he should be described as 'a scholar associated with the American Enterprise Institute', which emphasizes his political association with the libertarian-leaning think tank, or even as a 'leading scholar of American inequality', which emphasizes his intellectual contributions.

Choices over how to describe particular individuals are inevitable when writing about politics, and the distortion model assumes that journalists' choice of words reflects their own political preferences. A journalist with left-wing views will tend to see everybody else as comparatively right-wing, while a journalist with right-wing views will tend to see everybody else as comparatively left-wing. This kind of bias has previously been labeled *statement bias* [22].

Together, the three tendencies outlined above result in a consistent slant of media output in line with the journalist's political preferences. The model is illustrated in Figure 1. At each stage, some level of political bias enters into the journalistic production process, and that bias accumulates across the stages, resulting in output that becomes progressively closer to the journalists' own views.

2. Data Collection and Metrics

2.1 Data Collection and Initial Coding

We searched the published literature for surveys of journalists that included questions on voting behavior or vote intentions. This search yielded comparatively few relevant articles, and we therefore turned to works such as dissertations, reports, and newspaper articles. The reports were often written in the local language (e.g. French in France), and were often published by journalist associations or media organizations. In other cases, newspapers themselves conducted surveys and reported the results in their own pages, almost invariably in the local language.

To collect these data, we were assisted by a diverse team of international research assistants who could read the local language, and knew where to look or whom to ask. When we were unable to find anyone, we wrote to local journalist associations and relevant academics asking if they knew of any relevant sources. In general, our search was multi-faceted: Google Scholar, Google advanced search, asking friends from relevant countries, asking for assistance on social media platforms such as Twitter and Reddit, etc.

The resulting sources were saved to a publicly accessible repository at the Open Science Framework (https://osf.io/6uvnu/). Online sources were archived to prevent link rot or deletion of primary source material. Data from the sources were coded using a standardized format, and entered into a publicly accessible spreadsheet at Google Drive. Usually some adjustments to the data were needed, and these were done in a dedicated sheet within the spreadsheet so that everything was fully documented. The most common adjustment concerns respondents who declined to say or didn't know whom they had voted for. In particular, these individuals were ignored, and the definite preferences were normalized to 100% by dividing by the sum of the definite preferences. An example of this is shown in Table 1.

This method effectively assumes that people who didn't contribute data would have voted in the same relative proportions as their counterparts who did. In reality, this assumption is probably somewhat inaccurate, and one

1 The authors ran a correspondence experiment in which they emailed a large number of journalists on behalf of a fictitious candidate for the state legislature, and asked each one whether she would be able to cover the candidate. They found that journalists were not significantly more likely to cover the candidate when he was described as conservative, as compared to when he was described as liberal. However, we do not believe this provides compelling evidence for the authors' conclusions because it could be ideologically advantageous for journalists to cover a candidate from the opposing party. For example, it might allow them to misrepresent the candidate or to cast his views in an unfavourable light.

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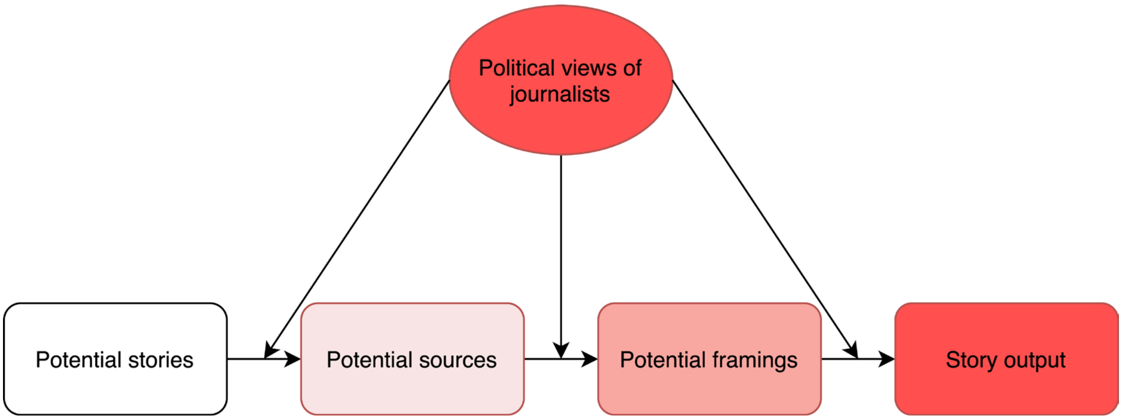

Figure 1. Sketch of the distortion model for the journalistic process.

Table 1. Calculation example for vote normalization. Polish journalists for 2005 parliament election (1st round).

Party	% of journalists	% of votes cast
Social Democracy of Poland	3	3.33
Democratic Left Alliance	4	4.44
Democratic Party	9	10
Civic Platform	60	66.67
Polish People's Party	0	0
Law and Justice	11	12.22
Self-Defence of the Republic of Poland	0	0
League of Polish Families	0	0
Real Politics Union	3	3.33
Total voted	90	100
Abstained	10	

can come up with hypotheses as to how the method might bias results either to the left or to the right [7,24]. One might expect a bias towards the political centre from the left because very left-wing journalists will decline to state their preferences, cognizant that the surveys will reveal the overall leanings of their profession, which would not be in their interest if they want to appear as neutral reporters of the truth. Alternatively, one might expect a bias toward the left from the right because right-wing journalists might not dare to state their true preferences even in anonymous surveys. It is possible to quantitatively analyze the question by examining whether surveys with more abstainers produced different findings than those with less, or by asking about voting intentions in more circumspect ways [25,26].

The sample size of the surveys included in our analysis had a mean/median of 542/500, with a range from 89 to 1640. The effective sample size (number with definite preference given) had a mean/median of 418/408 with a range of 72 to 1,338. The mean/median proportion of journalists who provided party preference data was 0.75/0.79 (sd = 0.17). On average, there was a mean/median of 2.5/1.0 surveys by country.

2.2 Relative Preference Metrics

To estimate journalists' political preferences, one needs a reference population to serve as an anchor. Since we had decided to focus on journalists' voting behaviour or vote intentions, we utilised data from the national election that was nearest in time to the relevant journalist survey. In a few cases, we averaged two elections equidistant in time (details are given in the Calculations sheet). Political skew was defined as any deviation of journalists' preferences from those of the general voting population. Of course, such skew could be in either one of two directions: journalists might prefer a given party more or less than the general voting population.

Because of disagreement about the optimal metric to use (the authors could not even agree), we decided on a pluralistic approach, and employed several metrics. First, we used the delta %point (*d*) metric. This is the simplest metric, and is defined as journalist% - general%, i.e., the number of %points that journalists vote more for a given party than the general population. When negative, it means that journalists vote for the party less than the general population. The metric could be seen as problematic for smaller parties because it fails to capture the relative aspect of party support. If journalists are 5 ppts more likely to vote for a particular party, it may matter whether that party enjoys 5% or 50% support in the general population.

The second metric we used is the relative risk (RR), which takes into account the relative party sizes. This is defined as journalist% / general%, and captures the differences in relative support. In the case of 0% support among the

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general population, the metric would be undefined. However, given that journalists are part of the general population, this scenario is impossible, and never occurred in our data. One problem with the relative ratio is that it is harder for larger parties to have high ratios than smaller parties. If a party is already at 20% general population support, the maximum RR is 5 because journalists cannot support it more than 100%. For a party with 5% support among the general population, a relative ratio of 20 is possible.

The third metric we used, which takes into account the reciprocal of support for each party, is the odds ratio (OR), defined as (journalist-support% / journalist-non-support%) / (general-support% / general-non-support%). This metric is commonly used when modeling binary outcomes for statistical reasons (e.g. as log odds in a logistic regression), but is less intuitive. The relative risk and odds ratio measures suffer from a non-linearity problem relating to the direction of coding. The RR can theoretically be almost infinitely large, but cannot be lower than 0. A solution for this is to log10 transform the metric. This results in a linear (i.e., interval) scale where a 2-unit decrease in the score has the same meaning as a 2-unit increase. Table 2 shows a few examples of the metrics.

Table 2. Example calculations of preference metrics.

Journalist%	General%	d	RR	OR	log10RR	log10OR
45	20	25	2.25	3.27	0.35	0.51
35	10	25	3.50	4.85	0.54	0.69
15	10	5	1.50	1.59	0.18	0.20
10	10	0	1	1	0	0
10	15	-5	0.67	0.63	-0.18	-0.20
10	35	-25	0.29	0.21	-0.54	-0.69
20	45	-25	0.44	0.31	-0.35	-0.51

None of the metrics are entirely satisfactory. For instance, while the log10RR takes into account the relative support without nonlinearity problems, it does not give any information about the overall importance of the difference. If a party has 1% support among the general population and 3% support among journalists, this would constitute a threefold difference in attitudes, but would not be very important in terms of overall voting behavior. The *d* metric would clearly show this, however, while providing less information about the differences in relative support. A difference in party support of 80% versus 90% might not be taken to have the same importance as a difference of 1% versus 11%, say, even though both differences have a *d*-value of 10% points. We decided to report detailed results from the *d* and log10RR metrics in the main text. Results for the other metrics can be found in our supplementary materials.

One particular problem with the log transformed metrics is that they are undefined when journalists have zero support for a given party in our samples. This problem arises due to sampling error for parties that have low levels of support among journalists (assuming that journalists never have exactly 0% support for a party). Thus, excluding the undefined data points would result in a data bias because of the excluded data's relation to the outcome of interest (i.e., there would be nonrandom missing data). We therefore conducted a simulation study to investigate the best way to adjust the data. We found that a local regression model based on sample size performed well. We imputed the best guess of support for parties where 0% was observed with a given sample size. After that, the support for other parties was adjusted downwards slightly so that the sum was again 100%. This essentially mimics a Bayesian approach with a weak prior. See the supplementary materials for more details about this procedure.

2.3 Party Data

Figure 2. Infobox on Wikipedia for Sweden Democrats (Sverigedemokraterna, https://en.wikipedia.org/wiki/

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Table 3. Political party ideology tag tabulation. LW = left-wing, RW = right-wing.

Rank	Tag	Proportion	Count	Rank	Tag	Proportion	Count
1	conservative	0.45	86	12	RW_populism	0.13	25
2	liberalism	0.40	76	13	democratic_ socialism	0.12	22
3	EU_positive	0.23	43	14	national_ conservatism	0.11	21
4	EU_skeptic	0.21	41	15	agrarianism	0.08	15
5	populism	0.18	35	16	feminism	0.07	13
6	green	0.18	34	17	communism	0.07	13
7	nationalism	0.17	33	18	libertarianism	0.05	10
8	social_ democracy	0.17	32	19	centrism	0.04	7
9	social_ liberalism	0.17	32	20	direct_ democracy	0.04	7
10	christian	0.15	28	21	LW_populism	0.03	5
11	socialism	0.14	27				

Sweden_Democrats).

By combining data from surveys of journalists and general elections, we computed metrics of relative support for political parties. There were 151 parties with at least one relative preference datapoint in our sample. By itself, however, this information is not informative. One also needs some information about the parties themselves. Instead of relying on the authors' judgment of party political ideology and relative placement (which could of course be biased), we relied on the English language Wikipedia as an external source. English Wikipedia has pages for all of the parties in our dataset (n = 197), and provides ideological and relative placement data in a semi-structured format called the infobox. We retrieved and processed this information automatically using a web scraper. Political left-right position data were available for 93% of the parties (n = 184), and political ideology data for 97% (n = 191). Missing data were mostly confined to small or defunct parties. Figure 2 shows a part of the infobox for a party (Sweden Democrats, from Sweden). The information of interest is given by *Ideology* and *Political position*. For political ideology, we cleaned the references (i.e., the numbers in brackets) and any explanatory text in parentheses (not shown in example). This results in a tag set for every party. The tags across pages were not entirely standardized, so to reduce the number of tags to a more manageable quantity, we recoded and merged a few of them. The details of this procedure are given in the supplementary materials. Table 3 shows the frequency distribution for the ideology tags.

For political positions, nearly all the descriptors refer to a relative position between far-left and far-right, sometimes with two descriptors being used (e.g. "right-wing to far-right"). In almost every case, we removed any other descriptions given, and converted the political position into a numerical scale from -3 to 3, reflecting the 7 possible descriptors used.[2] The descriptors were then averaged for each party. For parties with two listed, this resulted in half integer values (e.g. 2.5 for "right to far right"). Figure 3 shows the distribution of political positions in the data. The mean/median position was 0.05 with a standard deviation of 1.40 and skew of 0.01. Thus, it was nearly perfectly symmetrical despite having a bimodal shape. This seems to indicate a relative lack of bias in Wikipedia's positioning of parties, since bias would have presumably skewed the distribution in a particular direction.

2.4 Independent Party Ratings

To check the validity of Wikipedia's party ratings, we recruited 25 individuals to rate all 197 parties in our dataset on a 7-point scale from "far-left" to "far-right" (including non-integer values, if desired). These individuals were recruited online via Facebook groups for people interested in politics, and via participant referral (snowballing). Each individual received approximately 300 DKK (45 USD) for participating. Raters were told that they could use any approach they wanted, except that they should not use Wikipedia, and should not simply copy-and-paste ratings from another source, including another participant. They were not told the purpose of the study. 23 out of 25 raters were Danish (the remaining two were Dutch and Portugese, respectively); 60% were male; and they were aged between 17 and 30. The raters were

2 One party was described as "syncretic" which we also coded as 0.

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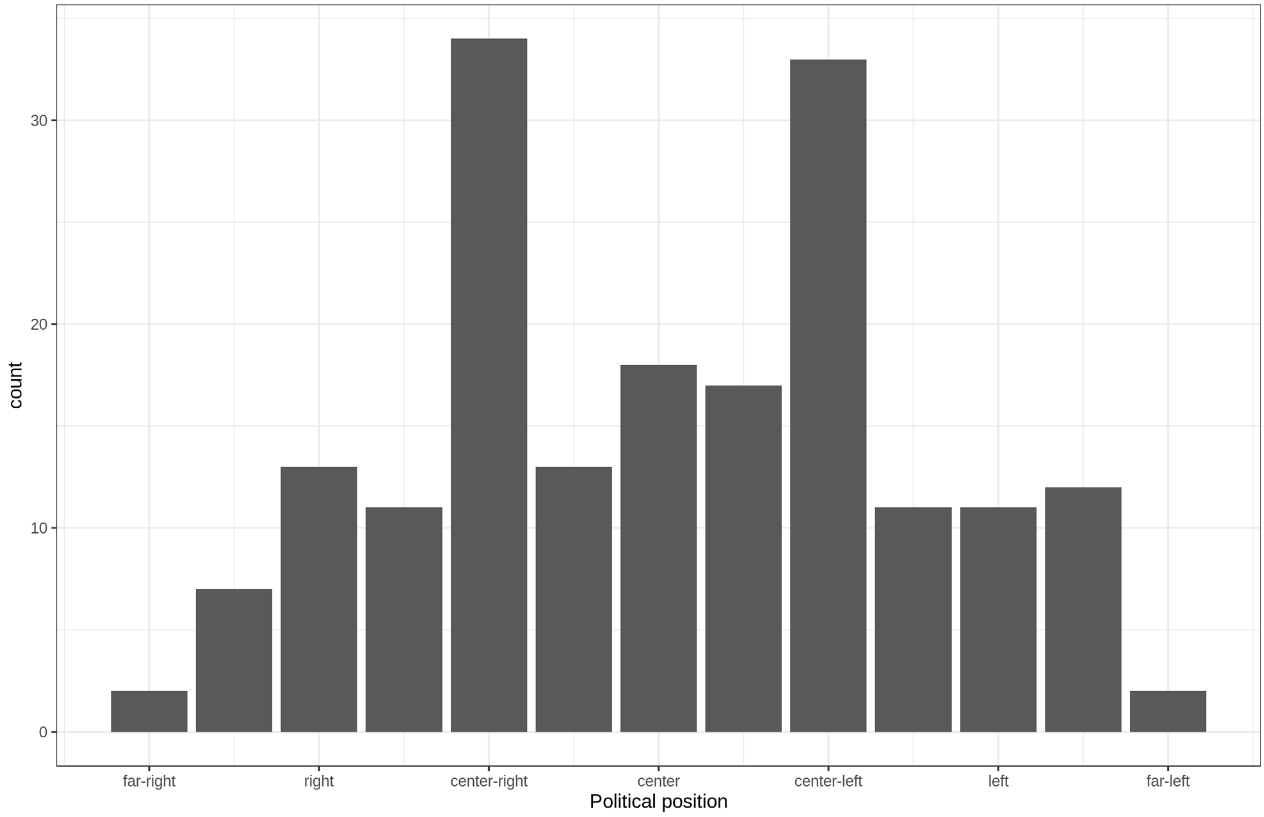

Figure 3. Political positions of parties according to English Wikipedia position data.

recruited by a research assistant who was also not aware of the study's purpose.

There was no evidence of cheating on the part of raters. No two raters were suspiciously similar in ratings (maximum r = .91, 2nd highest, r = .80, mean = .63), suggesting they had not copied one another. And none of the raters gave ratings that were suspiciously similar to Wikipedia's positions (maximum r = .85, mean r = .66), suggesting that they had complied with our instruction not to use Wikipedia. Measures of internal consistency for the average party ratings were good, although two of the raters gave ratings that were only weakly correlated with the others' (r's .15 and .36). The intraclass correlation was = .54 (.61 without two poor raters), Chronbach's alpha was .97 (.97 without two poor raters), and the median correlation was .61 (.63 without two poor raters). Clustering the ratings by similarity did not reveal any obvious effects of age, sex or Danish nationality.

Overall, the mean party ratings were strongly correlated with Wikipedia's ratings: across 183 parties for which Wikipedia ratings were available, r = .86, shown in Figure 4.[3]

One interesting difference between Wikipedia's ratings and participants' ratings is that participants labelled parties as "far-right" less often than Wikipedia. (Note the relative lack of parties in the top right of the plot). This may be due to our raters being slightly more right-wing than average, Wikipedia having a left-wing bias, or raters interpreting "far-right" as referring to Neo-Nazi parties, of which there are none in our dataset (their voter support was too low, and they were outlawed in some countries). Overall, however, the average participant ratings strongly corroborate the measures derived from Wikipedia.

2.5 Data Exclusion Rules

We excluded parties that received less than 2% in the general election. The journalist samples are generally too small to calculate accurate preference metrics for such parties, and they would therefore mostly contribute noise to the results. They are also of little practical importance since they enjoy no real political power in the countries where they are found.[4] This resulted in 19 excluded cases (of 151, 13%). As a robustness test, we analyzed the effect

3 The discrepancy with the number of parties in the Wikipedia data, 184, is that we mistakenly omitted one party from the list of parties given to the raters, and therefore have no rating data for this party (Pirate Party Germany). However, since the party in question is relatively minor, this omission is unlikely to have affected our results.

4 Most countries have election thresholds at higher values than 2%, with an average of about 4% across the countries in our dataset.

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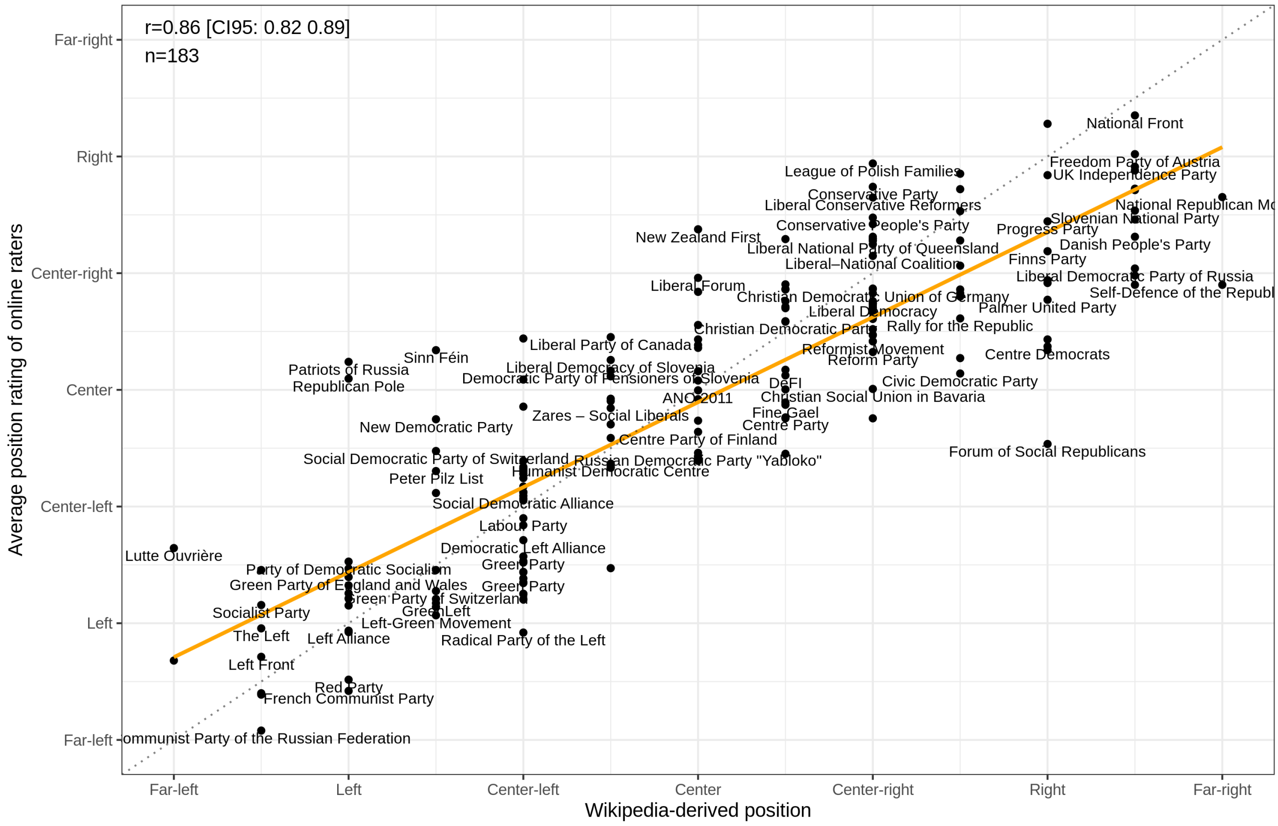

Figure 4. Wikipedia political positions vs. rater political estimates.

of this data exclusion, to be discussed later.

3. Analyses

There are a number of ways to analyze the dataset we assembled. The analyses reported here are to some degree exploratory because it was not clear how best to analyze the data before we gathered it, and we were therefore unable to pre-register our analyses [27].

To avoid giving more weight to parties for which we had multiple surveys, all voting data were averaged at the party level. In addition, parties were weighted so that each country had the same overall weight, at least initially (i.e. each party was assigned a weight of 1/n, where n is the number of parties with data for that country). This prevented countries with more parties from exerting a disproportionate influence on the results.[5]

3.1 Left-right Position

The simplest way to analyze the data is to examine the left-right position of parties, and the relative preferences of journalists for or against those parties. We report results based on both participants' party ratings and Wikipedia's party ratings. Our two preferred metrics, *d* and log10RR, are shown in Figures 5-8.

The figures indicate that there is a relatively strong relationship, whereby journalists tend to prefer parties with more left-wing positions overall. For Wikipedia's ratings: r = -.47 for *d*, r = -.53 for log10RR. And for participants' ratings: r = -.50 for *d*, r = -.53 for log10RR. In fact, the relationship was about equal in strength across all of our metrics and rating sources. For Wikipedia's ratings: r = -.48 for RR, r = -.40 for OR, and r = -.53 for logOR. And for participants' ratings: r = -.53 for RR, r = -.47 for OR, and r = -.54 for logOR. The relationship is somewhat nonlinear when using the Wikipedia data: the maximum differential in support is for center-left parties, rather than for far-left parties. A likelihood ratio test of a linear vs. nonlinear (spline) model supports this conclusion for the logRR metric and is borderline-significant for the *d* metric: d adj. R2 21.3% vs. 24.4%, p = 0.052; logRR: 27.4% vs. 31.7%, p = .016). The nonlinearity was not evident in the rater data (model comparisons p's .48 and .17, for d and logRR metrics, respectively).

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5 The election threshold (minimum vote% needed to gain any seat) has an impact on the number of parties that make it into a country's parliament. Since countries differ with respect to this threshold, some countries have a lot more unique, smaller parties, and others fewer and larger ones. The USA and the Netherlands represent the extreme positions on this since the USA has a de facto 2 party system and the Netherlands has no election threshold with 150 seats (i.e., one needs 0.67% of the vote to gain a seat).

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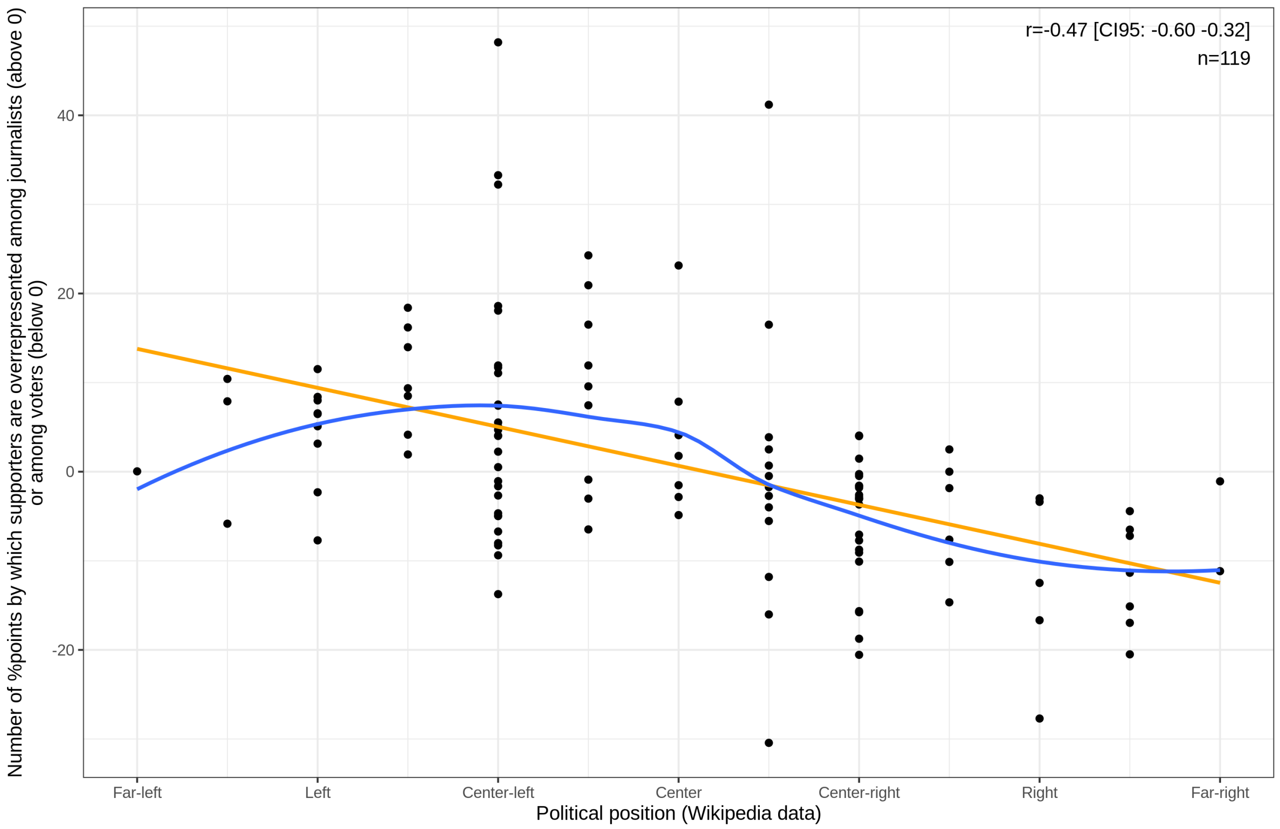

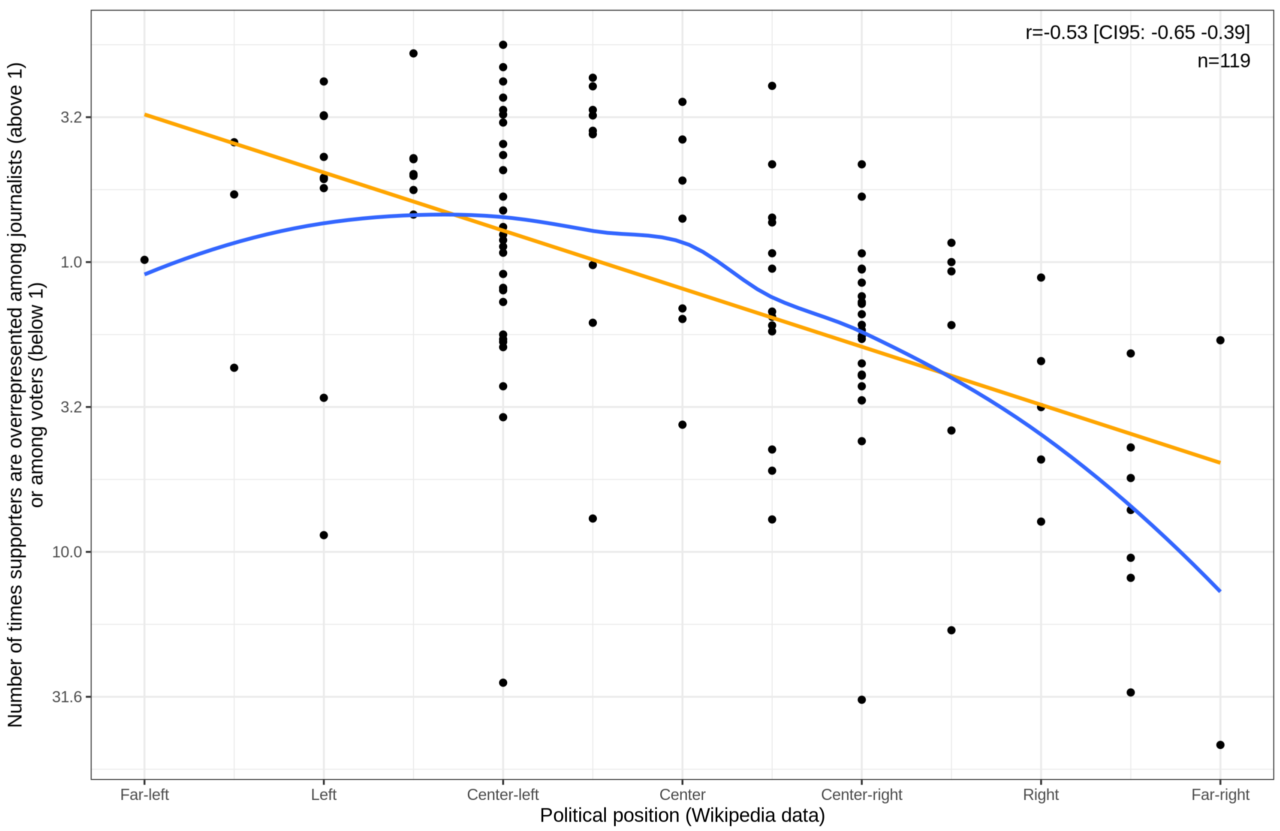

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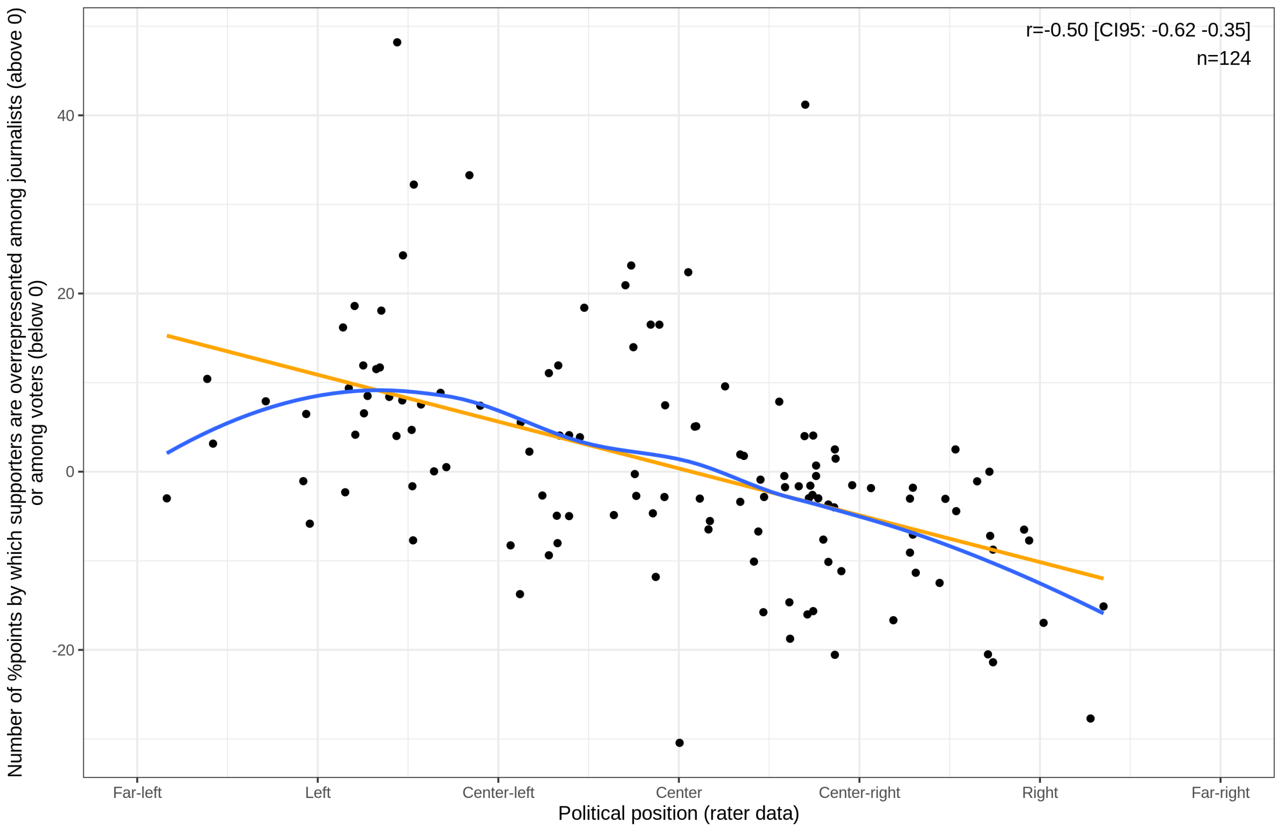

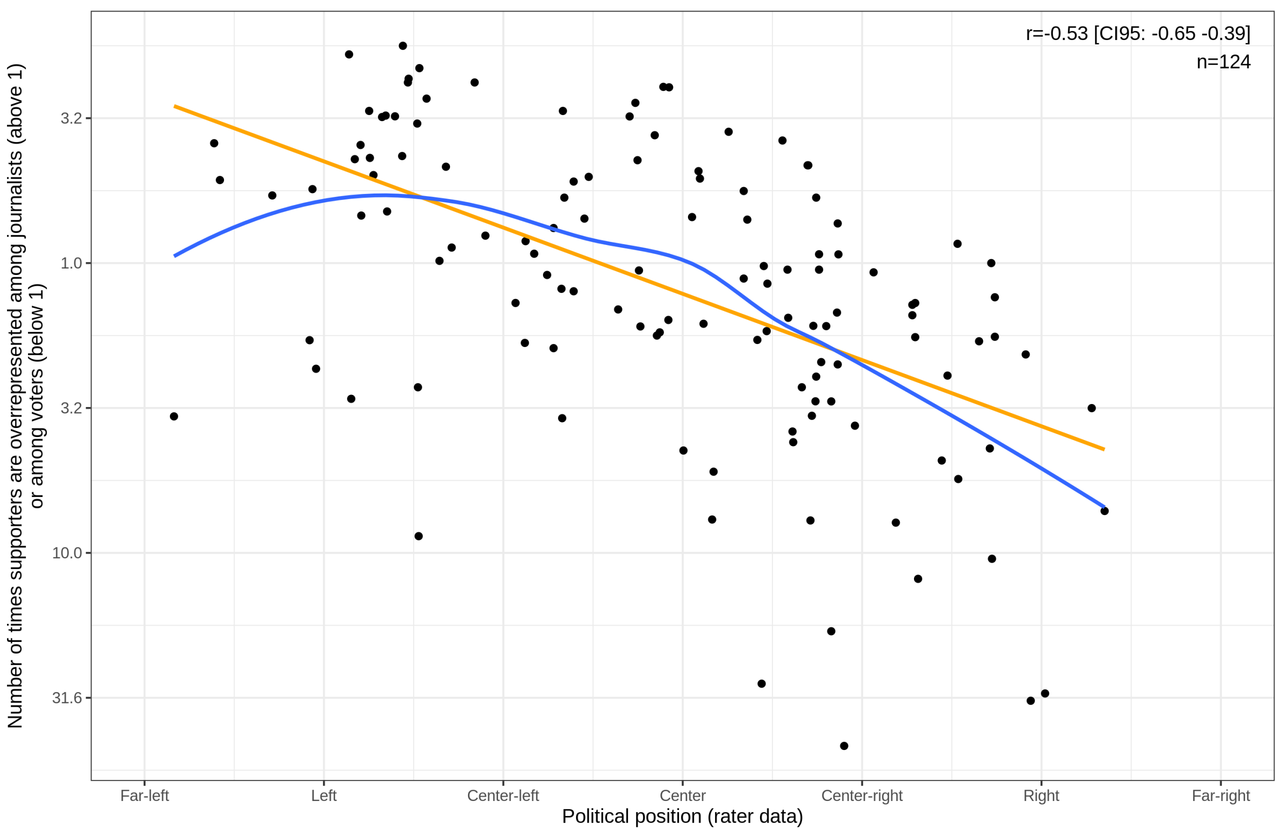

Figures 5-8. Party political position and journalists' relative preference for the d and log10RR metrics. Orange line = OLS fit, blue line = LOESS fit.

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3.2 Ideology Tags

Next, we turn to our ideology tags. Here we begin by taking a univariate approach, calculating an average (central tendency) for each tag. We chose the weighted mean and median as our estimators.[6] Figure 9 shows the results for the logRR metric.

Compared to the general voting population, journalists prefer parties that are associated with the following ideologies: green parties/environmentalism, feminism, support for the European Union, socialism. Conversely, journalists are less likely than the general voting population to support parties associated with the following ideologies: national conservatism, libertarianism, populism, nationalism and conservatism. Tables S1 and S2 in the Supplementary Information give the numerical results.

In some cases, the magnitude of journalists' relative preferences was quite large. Across the two versions of RR, the general population votes about 6.1 times more for national conservative parties as journalists do, whereas journalists vote about 3.0 times more for green parties.[7] For robustness, we analysed the data using unweighted versions as well as using the log10OR metric. However, doing so made relatively little difference to the results. The correlations across combinations of metrics were very strong with a mean/median correlation of r = .89/.91.

3.3 Multivariate Analyses

Having seen that both left-right position and most ideology tags are associated with journalists' relative preferences, we now tackle the more complicated question of how to combine the predictors into a single model. In particular, we have only about 120 cases with complete data, but 22 interrelated predictors. The predictors consist of the 21 tags and the overall political position, of which we have two versions. We also have three different outcome variables. Given these limitations, we did not expect to get useful results from OLS regression.

In macroeconomics, a similar issue arises when using country-level data. Consequently, some economists have begun using a Bayesian model averaging (BMA) approach[8] [28-31]. This method involves fitting all the possible regressions (where possible, otherwise sampling 1000s of them), and seeing which predictors tend to be included in the best models, and how strong they are in these models. It is conceptually similar to best subset selection [32], and is a form of meta-analysis [33]. We fit BMA to our dataset using the BMS package [34]. We used the default settings for the package, and analyzed the complete set of models since this was computationally feasible. In our case, there were 21-22 predictors yielding 2-4 million models to evaluate (runtime on a laptop was a few minutes for each set). We did this for each of the three outcome metrics (d, log10RR, and log10OR), and each of the two sets of political position data (Wikipedia and rater-based). We left out the populism tag because of its redundancy with respect to the directional populism tags (right-wing populism and left-wing populism).

Because the output from these analyses is rather lengthy, we have confined it to the supplementary materials (see Tables S3-S6). In an ideal world, there would be variables that are clearly important in all models, and variables that are not. In addition, the same variables would be important no matter which outcome metric, or which version of the political position data, we use. Unfortunately, our output tables showed that reality is not quite so clear. For example, in the first meta-analysis (Wikipedia data + d outcome) the 'conservative' tag variable was included in 97% of the best models. The effect size was quite large at -9.7 (i.e, journalists' vote% was 9.7% lower for parties tagged as 'conservative', holding the other variables constant). However, when we compared these results to the parallel results based on the rating data, we found that this tag was only included in 85% of the best models, though it still had a sizable beta of -7.7. And when we looked at the results based on log10RR, the same tag was only included in 93% and 66% of the best models (for Wikipedia dating and rating data, respectively). This shows that modelling choices matter for the stability of the results.

For the sake of simplicity, we looked for variables that appeared to be useful across the four meta-analyses corresponding to our preferred specifications (Tables S3-S4). We somewhat arbitrarily defined 'useful' variables as those that 1) had a PIP of at least 10%, and 2) had a post mean effect size larger than trivial (d > 1, |log10RR|

6 The unweighted median is the middle datapoint in a set of numbers ranked by value. If there are an even number of datapoints, the mean of the two middle datapoints is used. The weighted median works the same way, but applies the weights (1/number of parties in that country) to increase or decrease the relative size of each datapoint along the ranking, and then chooses the middle one as usual.

7 The outlier in the figure for the green tag is *Youth Party – European Greens*, from Slovenia (https://en.wikipedia.org/wiki/Youth_Party_%E2%80%93_European_Greens), which obtained anomalously low support among journalists in a sample of 300 journalists from 2009. As a matter of fact, the result is probably due to sampling error, given that the party received only 2.6% among the general population and 0.3% among the journalists. This is a difference of only a few individuals in the sample, and illustrates the extreme sampling error problem with the RR and OR metrics when the level of support for a party is low.

8 This method is also called Bayesian averaging of classical estimates (BACE), where classical refers to the frequentist approach in the source regressions.

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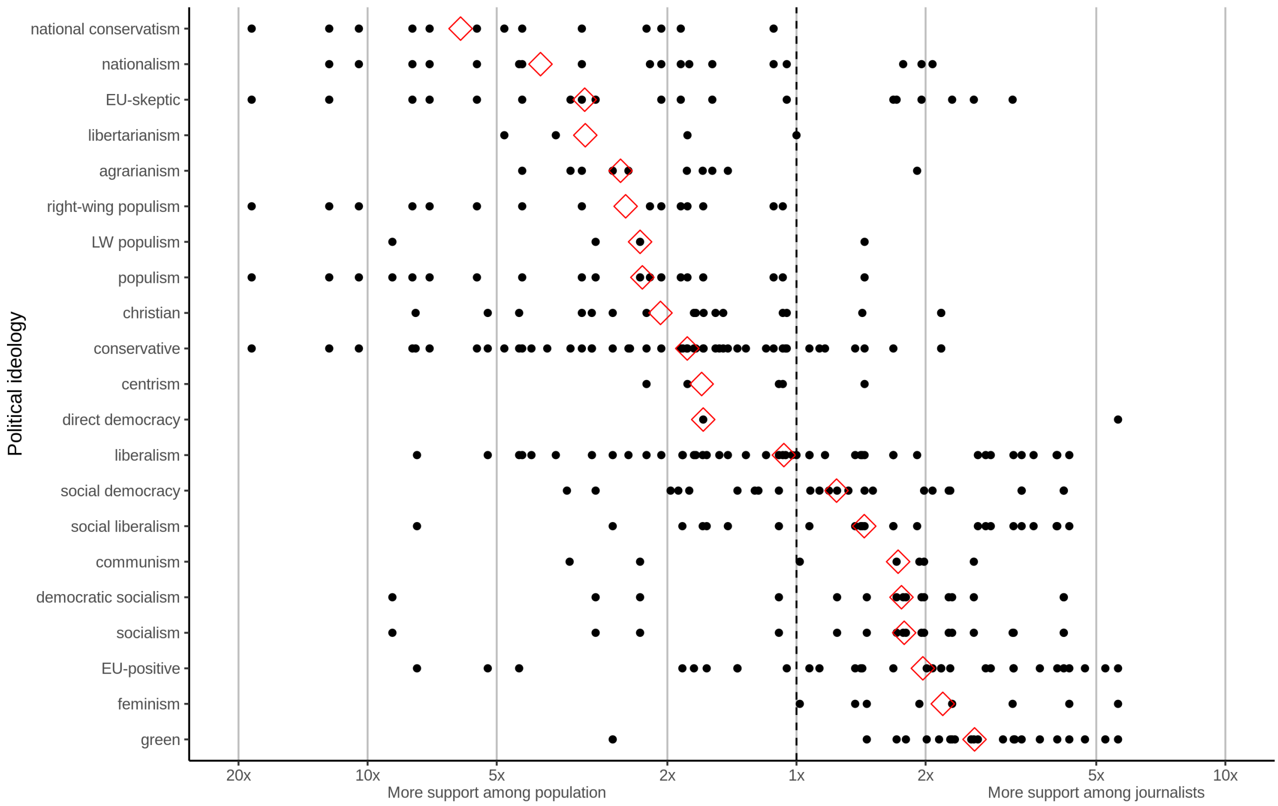

Figure 9. Journalists' relative support for parties by political ideology. Red diamonds correspond to the weighted median for each tag in the log10 RR metric.

> .05, i.e. 10% increase). Given these criteria, the most important variables were: 'conservative' (negative), 'nationalism' (negative), and 'green' (positive). Thus, our multivariate analysis shows that these seem to be the most useful variables that have an appreciable effect size. The conclusion is not necessarily that other variables don't matter, but just that their effects are difficult to detect with a high degree of confidence in the current dataset.

3.4 Left-right Position by Country

Using the party preference data and the political position of parties, it is possible to calculate the overall political position of the general population in a country, the position of journalists in that country, and the difference between them. The latter may be taken as an overall estimate of the left-right skew of the journalists in a particular country. However, given that some of the data on journalists were obtained from ad hoc samples, individual estimates are subject to considerable uncertainty, and should be interpreted with caution. Table 4 shows the values for the countries with available data, ordered by the magnitude of the skew.

Based on the Wikipedia data, it can be observed that, in 16 out of 16 countries, journalists are more left-wing than the general population of voters. The strength of this skew varies from -0.17 to -0.96, with a mean/SD of -0.58/0.26. If instead we look at the rater data, we see a left-bias for 16 out of 17 countries, with a mean/SD of -0.52/0.26. The only notable difference is that Slovenia has a very slight right-bias in the rater data, probably related to the issue with small parties we discussed earlier. It can also be observed that countries differ substantially in their mean political position, and that these differences make intuitive sense. Poland stands out in our dataset as particularly right-wing (0.98 and 1.11, respectively) and indeed, it is generally known as a conservative, Catholic country. On the other hand, the general populations in the Netherlands and Germany are rated as left-of-center in our dataset. This is somewhat puzzling for Germany, given that the country has been governed by center-right parties since 2005 (headed by Angela Merkel). Generally speaking, the results in Table 4 should be taken as a first attempt at quantifying the skew of journalists in different countries, and not as something definitive.

3.5 Robustness Checks

We have already seen that the tag-based results were fairly robust to the outcome metric and the use of weights

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Table 4. Average political position of journalists and the general population of voters, by country. Participant ratings were used to calculate positions. The ratings derived from the Wikipedia data correlated at r = .86 with these, but did not include the USA.

Political position and bias results by country								
	Wikipedia-based political position				Rater-based political position			
	Country	Journalist mean	General pop. mean	Bias wikipedia	Country	Journalist mean	General pop. mean	Bias
1	Austria	-0.36	0.62	-0.97	Austria	-0.77	0.33	-1.10
2	France	-0.73	0.20	-0.93	France	-1.08	-0.27	-0.81
3	Switzerland	-0.22	0.66	-0.89	Switzerland	-0.06	0.63	-0.69
4	Denmark	-0.75	0.10	-0.86	Denmark	-0.69	0.01	-0.69
5	Ireland	-0.66	0.18	-0.84	Ireland	-0.85	-0.26	-0.58
6	Sweden	-0.65	0.06	-0.71	Sweden	-0.85	-0.18	-0.67
7	Norway	-0.37	0.18	-0.56	Norway	-0.21	0.25	-0.46
8	United Kingdom	-0.31	0.23	-0.54	United Kingdom	0.01	0.52	-0.51
9	Poland	0.48	0.98	-0.50	Poland	0.70	1.11	-0.42
10	Finland	-0.26	0.24	-0.50	Finland	-0.64	-0.03	-0.61
11	Belgium	-0.46	0.02	-0.48	Belgium	-0.71	-0.14	-0.57
12	Netherlands	-0.59	-0.14	-0.45	Netherlands	-0.71	-0.21	-0.50
13	Australia	-0.11	0.24	-0.35	Australia	-0.17	0.25	-0.42
14	Canada	-0.30	0.01	-0.31	Canada	0.28	0.38	-0.10
15	Germany	-0.59	-0.38	-0.21	Germany	-0.69	-0.29	-0.40
16	Slovenia	0.19	0.35	-0.17	Slovenia	-0.06	-0.09	0.03
					USA	0.51	0.88	-0.37

(cf. Section 3.2). However, there are other decisions that might have influenced the results. (Note that we also compiled data on the political attitudes of other media personnel. These are provided in Tables S7-S8 in the Supplementary Information.)

First, recall that we used a pseudo-Bayesian approach to move the 0 values away from exact zero, so as to ensure that our RR values would be meaningful. (Observed values of 0 result in relative ratios (RR's) of 0, and thus infinite values for the log transformation.) We re-ran the main left-right analysis using the unadjusted values. This is straightforward for the *d* metric, and yielded very similar results, as expected (for the ratings data: r = -.50 before and after; for Wikipedia data, r = -.47 before and after). For the log10RR metric, this alternative specification yielded a small increase in effect sizes, due to the removal of many datapoints corresponding to right-wing parties with observed 0% support among journalists (n dropped from 132 to 120). The observed changes were quite minor, however: the log10RR left-right correlations changed from -.53 to -.55 for the Wikipedia data, and from -.53 to -.56 for the ratings data.

Second, recall that we excluded data for parties with very low levels of support in the general population on the grounds that these data would be afflicted by substantial sampling error. We examined the effect of trying different thresholds for exclusion, including none. Figure 10 shows the results across method choices.

Here we see that changing the threshold from 0 to 10% leads to an *increase* in the effect size, presumably due to removal of cases with large errors. At a threshold of 10% mark, only 59 cases out of the original 151 remain in the analysis. Thus our decision to only remove parties with less than 2% support seems to be a rather conservative choice that tended to weaken the results slightly.

Third, we tried dropping data from older sources. While we sought to identify the newest possible sources, especially surveys from the last 20 years, we sometimes had to rely on older sources. The publication dates of the surveys included in our analysis range from 1997 to 2017, but most of the data were of more recent origin: mean/SD = 2008/5.6. Did the inclusion of older data affect our results? If we drop the data from before 2005, the sample size changes from 132 to 100, and the results change from -.50 to -.55 (rating data, d metric), -.55 to -.58 (rating, log10RR), -.47 to -.50 (Wikipedia, d), and -.54 to -.57

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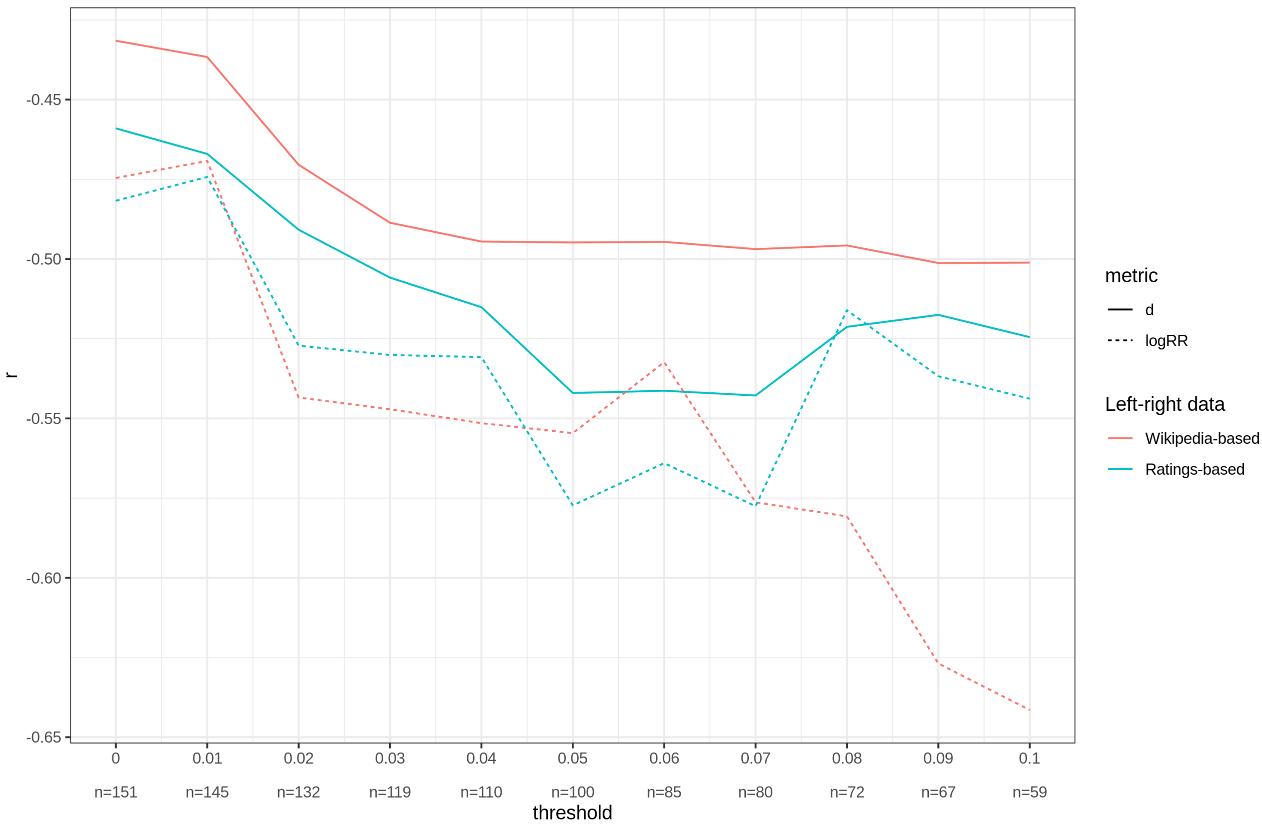

Figure 10. Left-right correlation results across minimum party support exclusion rule values.

(Wikipedia, log10RR). Hence there does not appear to be a notable effect of source age on our results. In fact, our inclusivity tended to weaken the results slightly.

4. Discussion and Conclusions

We have attempted to quantify the political skew of Western media by comparing survey data on journalists' voting behaviour to national election results. Our results showed that journalists lean left overall (Section 3.1), and that they are particularly unsupportive of national conservatism, while being particularly supportive of feminism, immigration and the EU (Section 3.2). In multivariate analysis using Bayesian model averaging (Section 3.3), we found that three ideology tags were consistent predictors: conservatism (negative), nationalism (negative), and green (positive). The findings we observed were generally robust to alternative specifications and sensitivity checks (Section 3.5). We believe they are unlikely to change much upon collection of additional data. Indeed, we wrote most of the analysis code early on in the process of data collection, and monitored the results as new data came in. The findings presented here are quite similar to those observed when data on only a few countries were available.

Of course, our analyses have a number of important limitations. First, not all the surveys of journalists had large sample sizes. Ideally, one would want a large, representative sample of journalists from each country. However, we often had to rely on ad hoc samples of journalists, (e.g. a survey from a particular region or city, or one based on a limited number of outlets.) The sample sizes varied from small (<100) to large (>1,000). The smaller surveys may of course yield uncertain estimates of journalists' preference for or against a given party. When we analyzed the effect of inclusion threshold, an indirect way of evaluating the effects of sampling error, we found that increasing the threshold did not weaken the results.

Second, many of the surveys were somewhat older than we would have liked. We attempted to find samples collected within the last 22 years (1998 onward) to reduce drift in party ideology between the time of the survey and the time party data were added Wikipedia. We only included older surveys when we were unable to find newer ones, based on the assumption that some slightly older data is preferable to no data at all for a given country. In addition, we did not find a substantial effect of sample age in our analyses.

Third, despite collecting data for multiple years, there were still some Western countries for which we were

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unable to obtain any relevant survey data. Unfortunately, these were not randomly located, but rather concentrated in southern and eastern Europe. The Southern European countries (Greece, Italy, Spain) were center stage in both the Eurozone debt crisis and the European migrant crisis, while the eastern European countries (Hungary, Czech Republic) have featured prominently in the news due to their opposition to accepting migrants. Hence it would be particularly interesting to assess the political skew of journalists in these countries. And indeed, it is possible that the political skew we detected would have been lower if data from more countries had been available. We hope that the present study will inspire further research on journalists' voting behavior, and reveal data sources that we missed.

Fourth, voting patterns reflect voters' political preferences, but they are by no means a perfect gauge of such preferences. While we were able to study several aspects of journalists' political attitudes indirectly through reported voting behaviour and vote intentions, some dimensions of their political attitudes were not covered at all, making it difficult to say precisely which way journalists lean on the relevant issues.

4.1 Journalists and Academics

Notwithstanding the limitations outlined above, we believe the empirical results we have presented are relevant to understanding the general flow of information within society. To explain why, it is necessary to expand our discussion to the political leanings of academics. Like journalists, academics mostly produce words for a living. Whereas journalists write news articles about current events, academics write reports about current research. Over the last few years, there has been a surge of interest in the political leanings of academics [24,35-38]. The results from this literature mirror those seen for journalists, but generally reveal even larger skews towards left-wing parties and political attitudes. For example, Langbert (2018) [24] found that the ratio of Democrat to Republican professors was 17.4:1 in History, 43.8:1 in Sociology and 133:1 in Anthropology.

The effects of political skews in journalism and academia may exert synergistic effects insofar as many news stories relate to findings from new studies published by academics. As a result, the process we described in the introduction (Figure 1) may lead to biased coverage of new research findings. One would expect journalists to preferentially report findings that comport with their own political views, and to interview sources who they suspect will give a favourable interpretation of the importance or validity of the findings. This tendency may interact with the scientific process itself, given that findings reported in the media receive more attention from scientists and tend to get cited more [39]-[41]. The academic performance of authors whose work is selected for coverage (quantified by means of citation indexes) will increase, and they will be likely to receive more funding for that line of research. This gives the authors an incentive to produce more research in the same vein. The process we have just outlined is illustrated in the flowchart shown in Figure 11.

It is important to mention that the potential impact of political bias is only statistical. Despite being left-leaning, the media and academia obviously produce many stories and research findings that are not "friendly" to left-wing causes. However, it is plausible that they produce fewer of these stories and findings than they would do in the absence of the observed political skew. This model is not a conspiracy theory because it does not postulate any secret coordination between large numbers of actors in different areas.[9]

4.2 Increasing Media Bias

Several studies have documented an increase in the left-liberal skew of Western media in recent decades [42-45]. But what factors may have given rise to such an increase, if it has in fact occurred? Shafer and Doherty (2017) [42] argue that the increase in political bias in the media is attributable to deep-rooted economic factors. They show that media personnel increasingly work in coastal areas which are left-wing. According to their calculations based on the U.S. Bureau of Labor Statistics employment data, the percentage of newspaper and internet-publishing workers working in a county where Democrats won increased from 61% in 2008 to 72% in 2016. Furthermore, the percentage of these individuals who worked in a country that was won by more than 30% points increased from 32% to 51%. Their results are even starker for internet media personnel: 90% of such individuals worked in a county won by Clinton, and 75% worked in a country where she won by more than 30% points. The reason for the increasing urbanization of journalists seems to be the expansion of national media at the expense of local media, which is presumably tied at least in part to the decline in advertising revenues for newspapers.

9 Note that there has been at least one case of large-scale secret collaboration, namely JournoList (Calderone, 2009). Ezra Klein (the former editor of Vox) ran a secret discussion forum (a Google Group) for several hundred left-leaning "bloggers, political reporters, magazine writers, policy wonks and academics". The individuals on this list sometimes worked together on pieces that later appeared in the news, and even plotted to collectively kill stories they considered damaging to their political goals (Strong, 2010).

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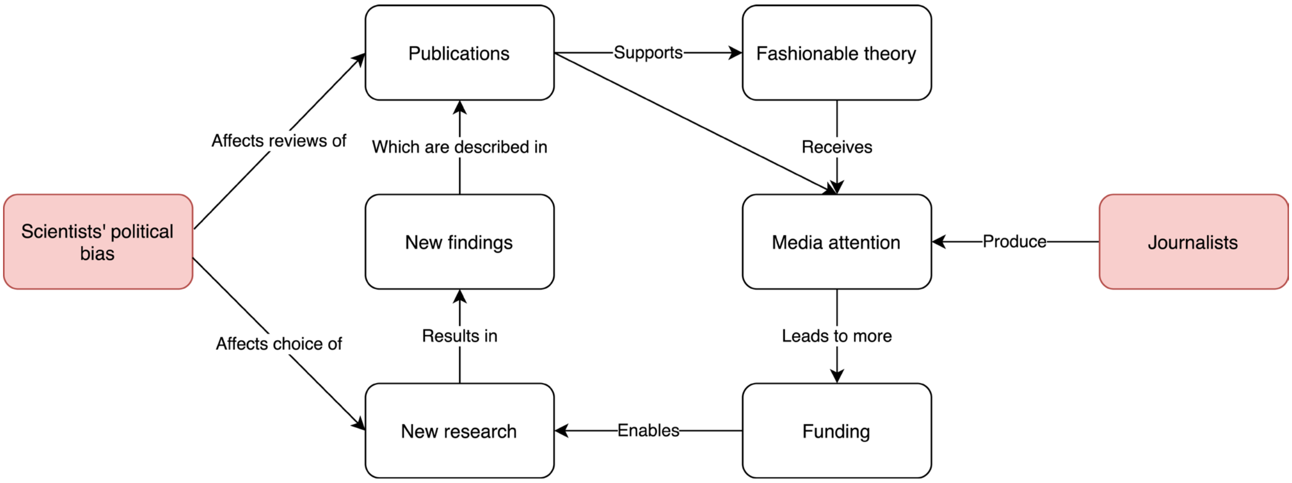

Figure 11. Flowchart of the scientific process with political bias of journalists and scientists.[10]

4.3 Proposals for Reducing Political Bias

Proposals for increasing political diversity among academics have focused on raising awareness and creating a more hospitable environment for dissidents [35]. We are not aware of any general attempts to increase political diversity among journalists, presumably because people prefer to choose from among an assortment of media outlets, each with a relatively obvious slant. One exception is the proposal mentioned by Groseclose (2012) [7]. Specifically, the Minneapolis *Star Tribune* ran an experiment where they hired a self-identified conservative to increase viewpoint diversity in their newsroom. As explained by Lambert (2007) [46],

> *When the tinny tinkle of "Joy to the World, the Lord Is Come" begins playing on the cell phone, everyone in range in the Star Tribune newsroom knows who's getting a call. It is Katherine Kersten, the paper's unapologetically religious and fiercely conservative metro columnist.*
>
> *Since May 2005, the Star Tribune has been engaged in what its top editor freely describes as "an experiment." The test has Katherine Kersten, a fifty-five-year-old former banker, and think-tank denizen, now an opinion writer, playing the role of an alien element injected into a tradition-bound newspaper culture.*
>
> *Long battered by conservative critics as the "Red Star" for its alleged knee-jerk liberalism ... the Star Tribune decided it had to answer. For the last twenty months, Kersten has been an one-woman solution, applying a decidedly different, and perhaps revolutionary, face to the role of big-city reporter and metro columnist.*

The presence of a single self-identified conservative in the newsroom means that anyone with a story that conservatives might prefer to see in print had a designated go-to person. Although this cannot by itself counteract the overall slant of a newsroom, it can at least ensure that every important "conservative" story has a chance of being told. Depending on how hiring usually works, this kind of low level affirmative action (keep at least one right-winger in the newsroom at left-wing newspapers, and vice versa at right-wing newspapers) might be a fruitful option for newspapers to consider.

Rather than trying to alter the ideological composition of the newsroom, one could attempt to forestall biases that may arise during the journalistic production process itself. In science, many such proposals have been made [35], and some have been partially implemented (e.g., registered reports). For example, one way bias distorts science is through what is termed *researcher degrees of freedom*, i.e., researchers can analyze their data in many different ways, and then only report the analyses that produced results favourable to their hypothesis [47-48]. Those results are then published, while the results from the alternative analyses, which yielded null or perhaps even negative results, remain unpublished. Because of the low evidentiary standards in social science, one can almost always find something in a given dataset that could be construed as supporting a particular hypothesis.[11] When the hypothesis under consideration has some relevance to public policy, as is often the case, this tendency may give rise to a general slant in the research findings.

Policies aiming to reduce bias in the journalistic

10 We acknowledge that a similar version of this chart was originally created by J.P. de Ruiter.

11 The reader can see this for himself by playing with the interactive p-hacking simulator at https://fivethirtyeight.com/features/science-isnt-broken/.

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production process have already been implemented in certain countries. In the US, for example, the equal-time rule was implemented as early as 1934 [49] (Miller, 2013, p. 359). This rule specifies that radio and TV stations must provide air time to opposing political candidates who request it. Of course, a detailed discussion how to counteract media bias is beyond the scope of this paper.

Supplementary Material and Acknowledgments

Supplementary materials including tables, code, high quality figures and data can be found at https://osf.io/6uvnu/.

We would like to thank numerous people who helped us gather data for the present study. Some of those who should have been mentioned by name declined due to fear of political retaliation by journalists, academics or both, underlining some of the points made in this article.

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