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Swedish Public Service: Politically biased or not?

Using text mining on political speeches to measure the political content in public service news articles

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Abstract

Public service in Sweden is supposed to be a politically independent source of information but in recent years this has been questioned due to its perceived left leaning by the population. In this paper the notion of a politically biased public service is studied following the approach by Laver et al (2003). A random forest approach was also proposed but with poor model performance. Parliament speeches between 2016 and 2021 were used to identify words and phrases with a political leaning to later use on article texts. Using the Laver method, a significant right bias can be found in most studied periods and the method performs well on positioning other news outlets relative to each other on a left-to-right dimension. The relative position of the public service SVT is to the right of all commercial news outlets, again suggesting a right bias in their news reporting. Further evaluation of the method on party speeches shows less convincing results, as all left speeches are calculated to be biased to the right. The reliability of the results should therefore be considered low.

Contents

1. Introduction

For several years there has been an ongoing debate on whether Swedish public service is politically biased. Especially since a study on the political preferences of employees in the Swedish public service showed that journalists support left parties to a much larger extent than the population in general (Asp, 2012). This discrepancy was shown to be even larger in public service, such as the public service television channel (SVT), which had over 80 percent in support of left parties. Another recent survey (Förtroendebarometern, 2021) shows that 39 percent of the population positioned SVT to the left on a left-neutral-right political dimension, compared to only 2 percent to the right. Early evidence from economic research also supports the existence of a left leaning bias in public service news reporting, at least in the British context (Crawford and Levonyan, 2018). This would be problematic, since one of the main purposes of public service in Sweden is to deliver information in a politically independent way to the citizens (Myndigheten för press, radio och TV, 2022). Debaters argue that if this purpose is not fulfilled, it could potentially have effects on the general political discourse and, as a consequence, also affect political outcomes. But the claim that the preferences of employees in public service actually affect the neutrality of public service news reporting in Sweden is still an unresolved issue. The aim of this paper is two-fold. First, it aims to answer the question of media bias in the news reporting of public service in Sweden. Second, it aims to investigate the relationship between any potential media bias and voter preferences. The following research questions will be analyzed:

1. Is Swedish public service politically biased, and if so, to what extent and towards what direction?
2. To what extent are voter preferences associated with a political bias in the public service?

In order to answer these questions, two main sources of data will be used. Transcribed speeches from politicians in the Swedish parliament, collected from the Parliaments database and news article data containing articles from SVT and three commercial news outlets from the database *Mediearkivet*. To measure the political content of an article text, words and phrases used more frequently by either left or right parties were selected as potential predictors of political leaning. After selecting the words and phrases, two methods to measure potential political bias will be used. The first one assigns a score of political leaning to each word and phrase based on the relative usage of them in the party speeches and then use these scores on the collection of article texts to give a measure of the aggregate political leaning. The second method is based on random forest classification models and classify article texts to be left, right or indetermined based on the combinations of words and phrases used in the text.

Some limitations of the paper need to be stressed. The set of words and phrases used is necessarily a small subset of all possible politically meaningful words and phrases. It is possible that the words and phrases that were selected in this paper are words that are less likely to be present in news articles than in political speeches and that another selection process with other words and phrases would give more accurate results. To alleviate this problem, different sets of words and phrases were used. Another limitation is that the sentiment in which words and phrases are used is not accounted for in any of the two methods. The use of a word or phrase will be interpreted the same, no matter if it is referred to in a negative, neutral or positive way.

The rest of the paper is structured as follows. In Chapter 2, previous literature and theory is presented and discussed. In Chapter 3, the data collecting process and data sources are presented. Chapter 4 introduces and explains the methodology used for analyzing the data. Chapter 5 presents the results and additional tests. Finally, conclusions are presented in Chapter 6.

2. Literature review and theory

This chapter aims to cover and discuss the relevant theory and literature connected to media bias. The chapter begins with a brief introduction to the field of media economics, moves on to present and discuss the literature and theories related to measuring bias, estimating media bias and estimating the effects of bias on political outcomes. Building on the concepts and theories in previous literature, a theoretical framework for the paper concludes the chapter.

Introduction to media economics

The field of media economics applies economic principles to issues related to the media market. The history of modern empirical research in media economics can be traced to the 1930s where economists studied the effects of propaganda from the Hitler and Mussolini regimes (Prat and Strömbäck, 2013). Since then, the field has expanded to a large body of literature covering topics such as media transparency, media coverage, media capture and media bias. Like many other fields of economics, theories in media economics have been influenced by theories and ideas from other fields, like journalism (McCombs and Shaw, 1973) and psychology (Kahneman and Tversky, 1984).

The first studies on the effects of mass media on political outcomes indicated that it had a relatively small effect on how people voted and that propaganda movies failed in its goal of indoctrinating the public (Prat and Strömbäck, 2013). New theories were developed and in the 1970s and 1980s strong evidence for them were found. One of these theories was the role of agenda setting, which hypothesized that people will conceive an issue or topic to be more important if it gets more coverage by the media (Prat and Strömbäck, 2013). In 1972, McCombs and Shaw published their paper on the agenda-setting function of mass media. In their seminal paper they analyzed how the content in mass media affected randomly selected voters on perceived key issues in the 1968 presidential campaign. They found that voters' perception of key issues was highly correlated with the issues highlighted in mass media, indicating that agenda-setting plays an important role in political outcomes. Another theory that gained interest during this time was the theory of framing. This theory refers to the idea that the way information is reported will influence how it is perceived by the public. In 1984, Kahneman and Tversky published their paper Choices, Values and Frames. In the paper, previous axioms of rationality were challenged, and one of the main findings was that questions of equal outcomes will be answered differently depending on how they are framed.

Theory & previous research

In the theory of media economics, the presence and amount of bias in news is seen as an equilibrium result of demand and supply factors. Consumers may prefer news which align closely to their own ideological preferences, or they may prefer unbiased news. Advertisers in newspapers want to reach consumers with a high purchasing power and news outlets may respond to this by aligning their content towards this part of the population to increase their add-revenues. News producing firms may be profit-maximizing or they may be willing to forego some of their profits to better align its content with the owner´s preferences. Journalists and editors may be willing to accept a lower wage if they are free to write in line with their own preferences and news outlets may respond to this by allowing lower revenues to lower its costs. The presence and amount of bias will in this setting be decided by the relative strength of these mechanisms. (Puglisi and Snyder, 2015). This view is well-established in the literature and differ mostly in their underlining assumptions of how agents act and in what factors they study.

In the literature on media bias, many different types of biases have been studied. In a survey by Prat and Strömbäck (2013), four different types of biases related to media are defined: Issue bias, facts bias, framing bias and ideological stand bias. Both issue bias and facts bias are related to the question of what is reported by the media. No media outlet can report everything and must select what issues to cover (issue bias) and what facts to include in their reporting (facts bias). Framing bias and ideological stand bias on the other hand is related to the question of how news are reported by the media. Framing bias builds on the idea that information given in different ways will be interpreted differently by the receiver (see Kahneman and Tversky, 1984), while ideological stand bias refers more explicitly to the way news are commented. Another problem that needs to be addressed is how bias can be measured. Puglisi and Snyder (2015) provide a summary of common measurements for media bias used in the literature. They stress that there is no easy way of measuring bias in an objective way and that to measure bias one always needs to answer the question of bias in relation to something. Most measures found in the literature restricts the analysis to a left-to-right political dimension. Common measures are to place media outlets in relation to the average or median voter, or to place them in relation to the average congressman in the parliament. Puglisi and Snyder also distinguish between explicit and implicit measures of bias. Explicit measures of bias are measures that try to capture bias that should be possible for consumers to detect. Erikson (1976) measured explicit media bias by looking at endorsements from local newspaper in the U.S. presidential election of 1964.

The study covered 223 counties and found effects on voting outcomes. An endorsement for the democratic candidate of a local newspaper was associated with a five percentage points higher voting for this candidate. Erikson argued that the findings showed evidence of newspapers' importance on voting outcomes in presidential elections in the U.S. More recently, Ansolabehere et al (2006) investigated this more in depth. Their study covered state and federal elections between 1940 and 2002. They highlight two important developments of political endorsements in the U.S. Endorsements in the 1940´s and 1950´s favored republican politicians, but that the endorsements slightly favored democratic candidates since then. Further, the paper found that newspapers have become much more likely to endorse incumbent politicians than in the past. The share of endorsements going to incumbent politicians in the 1940´s was about 60 percent compared to 90 percent in the early 2000´s. Butler and Schofield (2010) take another approach to measure explicit bias. In the presidential elections of 2008 letters supporting Obama and McCain were sent out to editors of newspapers around the U.S. They found that pro-McCain letters were more likely to be published. Further, letters supporting the candidate not endorsed by the newspaper was also more likely to be published, indicating that editors may act to balance bias.

The other category of measures, implicit measures, instead aim to capture more subtle types of biases. The two main approaches to measure implicit bias found in the literature is: the comparison approach and the issue approach. The comparison approach compares the text in news to text or speeches by actors of known political affiliation and places news outlets according to which actor they are most similar. The issue approach instead builds on agenda setting theory and aims to measure coverage of politically relevant topics that benefit different parties or groups. The approach of measuring media bias used in this paper draws from the literature using the comparison approach, and thus aims to measure implicit bias. This approach has its roots in political science literature but in recent years it has also been used and developed for the purposes of media economics. The comparison approach generally uses automated text analysis to compare the content of different texts. One of the first papers in economics to use the comparison approach to estimate media bias was a paper by Groseclose and Milyo (2005). They used data on citations of think tanks and policy groups among 17 media outlets and the congressmen in the House of Representatives between 1990 and 2003. The news articles included in the sample were restricted to news content and excluded editorial content and the like. First, the average ideological position (ADA score) was calculated for each think tank and policy group based on the number of non-negative citations from congressmen with known political affiliation. Next, news outlets were scored based on their citations of think tanks. They found that most of the studied news outlets were biased to the left of the average congressman. Only Fox News and Washington Times had a bias towards the right. Gentzkow and Shapiro (2010) use a similar approach but extends the analysis from think tanks to the usage of republican and democratic phrases. They used speeches of congressmen from the House of Representatives in the U.S to identify phrases that were used more frequently by republicans and democrats. Phrases of two or three words are extracted from speeches by congressmen after the removal of stop words. The phrases were then restricted to appear in at least 200 but no more than 15,000 newspaper headlines. At this stage Pearson's chi-square test statistic was calculated for each phrase and only the 500 phrases with the highest test statistic values of each phrase length were retained. Based on the frequency with which congressmen used these phrases, they were positioned on a republican-democrat dimension. The same scoring method was then used to place media outlets on the same dimension using the phases found in their news articles. In the same paper, Shapiro and Gentzkow went on to study what drives the bias. By using zip-code level data on circulation for local newspapers they were able to link consumer's political preferences (voting behavior) to the estimated bias. They found that political preferences of the consumers explained about 20 percent of the bias in local newspapers. On the other hand, ownership's preferences, measured as political donations of the owner, had no significant effect on ideological bias of newspapers. The findings support the idea of demand driven bias but were unable to find enough evidence for supply driven bias.

The literature concerning media bias in public service is scarce but there are some papers which have been published. One example of this is Crawford and Levonyan (2018). They used a method developed by Laver et al (2003) and compared the language in transcripts from BBC news broadcasting to political speeches given by Conservative or Labour in the UK parliament between 2013 and 2016. First, they computed how often each phrase was used by representatives from the two parties and assigned a score of slant (bias) based on these. Then the bias in BBC broadcasting was estimated by multiplying the times each phrase was used with the score associated to each phrase. The slant scores for the BBC showed a significant Labour-leaning slant in all periods except for the period after the 2015 election, indicating a left-leaning bias in the UK public service.

This section has highlighted some of the measures commonly used in the literature and the most relevant results found on the presence of and amount of bias in news media. Papers using both the measures of explicit and implicit bias find evidence supporting that bias exists. The methodology used to measure bias have relied solely on counting word or phrase frequency and in some cases assigning a score to these phrases to discriminate between the importance of them. No paper has considered to use more sophisticated models to also consider that combinations of different words and phrases in a document could be even more powerful to measure the political leaning of a news article. One of the aims of this paper is to deal with this gap by using a machine-learning algorithm (random forest). The results from the random forest models will then be contrasted to the results obtained by using a similar approach as in Crawford and Levonyan (2018). Additionally, this paper will add to the scarce literature on media bias in public service.

Effects of media bias on political outcomes

As have been demonstrated in the previous sections, there is strong evidence to support the idea of existing bias in mass media, especially at the individual news outlet level. The relevance of this bias for economic research hinges on the potential effects on society. Many studies have been trying to answer this question and this section aims to present an overview of this research.

Gerber and Karlan (2009) takes an interesting approach to capture the effects of media bias on voter outcome. Before the Virginia gubernatorial election in 2005, individuals were randomly assigned to a free subscription of Washington Post, Washington Times or to a control group with no free subscription. Washington Post is widely recognized as a more liberal newspaper, while Washington Times instead is recognized as a more conservative one. After the field experiment, a significant increase in support of the democratic candidate was found in both subscription groups. No significant differences were found in the level of political knowledge, political opinions and voter outcomes between the two groups. An explanation for this, proposed by the authors, was that the republicans had a difficult time during this period and that the issues covered mattered more than how it was reported. This would indicate that issue bias could influence voter outcomes. DellaVigna and Kaplan (2007) study the potential impact of biased media with another approach. They used data on entry to the cable network on a local level by the television channel Fox News between 1996 and 2000 and measure the impact on voting outcomes. Fox news is viewed as a conservative television channel and the authors used this as a source of increasing right-leaning bias in the market where Fox News entered. The results showed that in markets with Fox News, the channel contributed between 0,4 to 0,7 percentage points to the republican presidential candidate. A similar voting effect was found for senatorial elections, which were not covered by Fox News. Another paper (Snyder and Strömbäck, 2010) study the effects of issue bias on political outcomes. By using exogenous variation in local press coverage of congressmen in the house of representatives, they were able to study how this affects the level of political knowledge among citizens and how it affects political outcomes. They found that citizens with less local press coverage of their representatives were less able to name their representatives and to rank them. Related to issue bias, Eisensee and Strömbäck (2007) study the importance of coverage for U.S. relief to natural disasters between 1968 and 2002. They used exogenous variation in coverage by comparing the coverage and probability of relief aid when disasters occur simultaneously as other big news events such as the Olympic games. They showed that a high coverage of disasters is positively associated with the probability of receiving U.S. relief aid. The difference between the highest coverage and the lowest coverage was estimated to increase the likelihood of relief with eight percent. The effect of less coverage of natural disasters during Olympic games was estimated to a five percent lower likelihood of receiving U.S. relief. The main explanation put forth by the authors was that some news has a crowding-out effect on the coverage of other news. The paper clearly shows a link between coverage by mass media and political outcomes.

There is strong evidence for the notion that media bias could play an important role for political outcomes. The results are mixed with respect to if voters become more informed about their politicians but suggest that especially issue bias can play an important role both in voter outcomes and in decisions taken by politicians.

Theoretical framework

This section will present the theoretical foundation on which the paper rests. Relevant theory and concepts have already been presented in the previous sections and will form the basis of discussion for the theoretical framework.

The choice of how to measure bias is instrumental to any research studying bias. Most of the time it has been studied by comparing the news reporting on two sides of politics, for example on the usage of politically slanted words or public endorsements to politicians. If a significant difference is allocated to either side, this difference is generally regarded as a political bias towards that side. It needs to be stressed that this is one definition of what can be interpreted as political bias in news reporting, certainly not the only one. But, as mentioned above, bias must be defined in relation to something and this is one of the most common ones. Therefore, bias will be defined in this way also in this paper. However, in the Swedish case, the political system is somewhat different from those in which political bias has been studied in previous papers (predominantly the U.S. and the U.K.). The Swedish parliament is represented by eight parties, all of which need to be included in the analysis for a full analysis of potential political bias in news reporting. To solve this problem, each party will be assigned to have a certain political position on this left-to-right dimension, based on survey data that will be presented shortly. Two slightly different left-to-right dimensions will be considered in the later analysis. The first one is a binary dimension, where all parties assigned to the left will be regarded as an entity with a left orientation and vice versa for the parties assigned to the right. The second one is a non-binary dimension, where the exact position of a party on the left-to-right dimension will be used.

Another consideration that needs to be addressed is the setting in which public service operates compared to the setting of commercial media. The factors that drive media bias in public service is likely to be very different than those in the commercial setting. Public service is not dependent on sales or add revenues and are therefore less likely to be affected by demand factors. Any media bias found in the public sector is thus likely coming from supply factors. From the supply side, generally two important factors introduced above are considered: owner´s preferences and preferences held by journalists and editors. Since the public sector in Sweden has as its main purpose to deliver a neutral perspective on information, it is unlikely that owner's preferences are a strong driver of any bias. In fact, if the objective is successful to some degree, it should decrease any potential bias from other factors. The factor left to examine is the supply driven bias from the journalists´ and the editors´ preferences. These employees in the public sector also have preferences regarding political issues and can be placed along the left-to-right dimensions mentioned above. This reasoning leads to the interpretation of any potential bias being found in this setting to come from a supply driven bias from journalists and editors working in public service.

3. Data

Data collecting and processing

In this section the data collection procedure together with the processing of raw data will be covered. The section is divided into four parts and starts by describing this process for the data on political speeches, continues with the data on news articles, moves on to the data on political positions of parties and ends with the data on opinion polls.

Political language

Texts containing political language was collected in text format from the Swedish parliament (Riksdagen, 2022). Transcribed speeches from this source are available as far back as 1993 up to present day and can be found in the open database of the parliament (Riksdagen, 2022). The choice of using transcribed speeches from the parliament as a proxy for political language has been used in previous papers (see Groseclose and Milyo, 2005; Gentzkow and Shapiro, 2010). The raw data contain the transcribed speeches together with additional information on political affiliation and date.

All transcribed speeches between September 2016 to September 2021 were downloaded and amounts to a total of 60,249. All speeches containing less than 400 characters were dropped. This was done to exclude speeches with insufficient political content and speeches of the more formal character such as short responses and speeches not likely to contain enough information. In the next step, all speeches not held by a member of a specific party in the parliament were dropped. This includes but might not be limited to members of the parliament who have left their political party, the chairman and the king. Since these speeches does not have any clear political affiliation, they were excluded from any analysis. At the same time, text not referring to what was said in the speech was removed (page breaks etc.). After this processing of the raw data, the dataset contains a total of 58,190 speeches representing 96,6 percent of all speeches held in the parliament during this period.

News article data

The data used for news article texts was collected from the database Mediearkivet (authors own translation: “The Media archive”). Mediearkivet is provided by the Retriever group and is the largest source of news articles in the Nordics (RetrieverGroup, 2022). The article texts are not easily downloadable in bulk and thus Python was used to scrape the most important content of the articles of interest, including the article text and date. For scraping the data, the Python package Selenium was used. The sampling frame for articles was restricted to between

September 2016 to September 2021 for articles from the public service (SVT). Articles from commercial news outlets were also collected from September 2020 to September 2021 for the purposes of sensitivity analysis and further analysis of the nature of the bias being studied. The commercial news chosen were *Aftonbladet*, *Svenska Dagbladet* and *Dagens Nyheter* and were chosen based on their reach and their different political leanings. A measure of the political leanings of the news outlets was taken from the survey Förtroendebarometern (2021) and is presented in Table 3.1. From this survey there is one clear left-leaning news outlet, Aftonbladet, and one clear right-leaning news outlet, Svenska Dagbladet. The majority perceive SVT and Dagens Nyheter to be neutral news outlets but with a stronger perception to the left for SVT and a stronger perception to the right for Dagens Nyheter. This data will be used in later discussions about the reliability of the results.

Table 3.1: Perception of political leaning of news outlets by voters

News outlet	Left	Neither	Right
Aftonbladet	0.66	0.29	0.05
SVT	0.39	0.59	0.02
Dagens Nyheter	0.18	0.50	0.32
Svenska Dagbladet	0.07	0.41	0.52

Source: Förtroendebarometern (2021)

When scraping the news article data from Mediearkivet, the database offers a filter on articles based on topics available from around 2019. Whenever filtering on topics was available, the sampling frame was restricted to six topics {*Politics*, *Crime and Justice, Economy and Business*, *War and conflict*, *Accidents and natural disasters*, *Social conditions*, *Education*, *Working life*}. Examples of topics not included in the sampling frame were *Sports*, *Entertainment* and *Weather*. The topics were chosen based on what type of articles that are most likely to contain any political content. Any analysis concerning articles from before 2019 contain the full sample of articles since filtering was not available. The main reason behind restricting the sampling frame was time constraint. Not imposing any restriction on the sampling frame would have resulted in a considerably shorter time span in the longitudinal dataset for SVT or fewer commercial news outlets in the cross-sectional dataset and would likely not result in any substantial gains in information on potential media bias. Some limitations and problems with the scraping scripts need to be stressed. A small fraction of the total articles was not read at all. Possible explanations for this are a temporary loss of internet connection or a slower than usual response time from the database. Another error that occurs more frequently is that the code was not able to find the full article text. By manual inspection of these cases, the most common explanation is that the article that is read is on the front page and thus only includes a title. Another explanation could again be a temporary loss of internet connection or a slower than usual response time from the database. To minimize this problem, a waiting time for loading articles was included in the script which by manual inspection seems to have reduced this problem significantly. One last problem that arose while scraping was that the database stops loading the next page of results after 100 pages. This results in duplicates of articles from the 100th page. This was resolved later in the processing stage by removing duplicates from the dataset.

Ideological positions of parties

The ideological positions of parties were collected from a study made by Oscarsson and Svensson (2020). In the survey the respondents are asked to place each party in the parliament on a left-to-right dimension. The measure starts from 0 being far left and ends at 10 being far right. The political positions of parties used later in this paper are based on this survey, all parties scoring less than five were placed in the left group and all parties scoring more than five were placed in the right group. The perceived position of each party in this survey is presented in Table 3.2. The left parties by this division were Vänsterpartiet (V), Miljöpartiet (MP) and Socialdemokraterna (S), while the right parties were Centerpartiet (C), Liberalerna (L) (early in the sample of speeches: Folkpartiet), Kristdemokraterna (KD), Moderaterna (M) and Sverigedemokraterna (SD).

Table 3.2: Perceived political positions of parties:

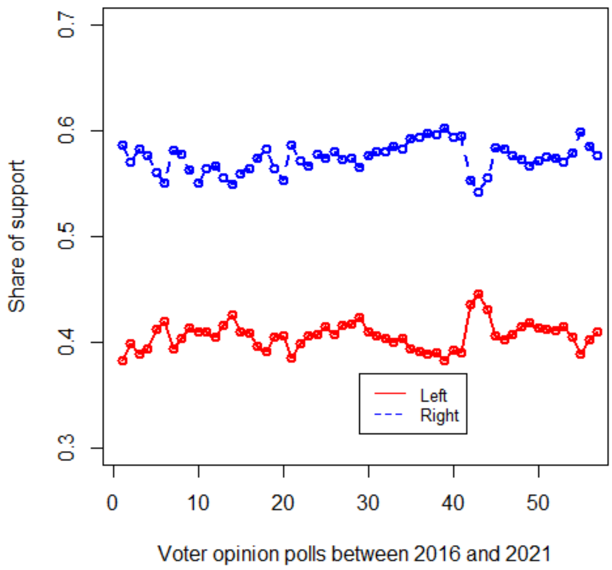
Party	V	MP	S	C	L	KD	M	SD
Perceived position	1.1	3.26	3.53	5.38	5.94	7.5	8.08	8.32

Source: Partiernas vänster-högerpositioner 1968-2019 (Oscarsson and Svensson, 2020)

Opinion polls data

The data used to identify voter preferences was collected from the Kantar Sifo´s monthly opinion poll survey *Väljarbarometern* (Kantar Sifo, 2022). The survey is the largest monthly survey of Swedish voter opinion and covers every month of the year except July. The survey is based on interviews of Swedish voters during a short span of days before the survey is published. In the survey the participants answer the question: *What party would you vote for if it was an election for the parliament today?* (authors own translation). After collecting the data, it was merged into a longitudinal dataset spanning from September in 2016 to October in 2021. Figure 3.1 presents how the voter opinion in Sweden has developed. In the graph, the left and right parties have been aggregated according to the data presented above in Table 3.2. The opinion polls data will later form the basis of the periods in which bias will be studied. Each period in the later estimations will be based on the articles published between two opinion polls. One period is about a month, except for the first period of just eighteen days and the period between the June and August which are always two months. The full sample contains 56 periods, spanning from September 2016 to September 2021. The opinion polls data with exact percentage shares and the dates when they were published can be found in Table B1 in Appendix B.

Figure 3.1: Voter preferences for left and right parties between 2016 and 2021



Source: Väljarbarometern (Kantar SIFO, 2022)

4. Methodology

In this chapter, the methodology to analyze political bias in news reporting will be presented and explained. The chapter begins by describing the selection process of potentially informative words and phrases to estimate and predict political leaning. After this, two different methods to estimate media bias will be presented. The first method was developed by Laver et al (2003) and later applied also by Crawford and Levonyan (2018), from now on referred to as the Laver method, will be presented starting on page 15. Similar approaches, based on frequency counts of words and phrases, have been used in many previous papers on media bias (see Gentzkow and Shapiro, 2010; Groseclose and Milyo, 2005). The other method has never been used before for measuring bias in news reporting (to the authors own knowledge). It is based on using the machine-learning algorithm random forest, which has been proven to be successful in many other settings. This method will be referred to as the random forest method and will be presented starting on page 21.

Before any further processing of the speech texts, they were randomly assigned to a training set and a test set. This is common practice when building classification models like the random forest (Weiss et al, 2010; Kuhn and Johnson, 2013) and is done to separate the process of finding patterns in texts and evaluating the performance of the two methods. Out of the total sample of speeches, 80 percent of the speeches were assigned to the training set and 20 percent to the test set.

The selection process of words and phrases

This section will describe the text analysis process of selecting words and phrases to use in the later analysis. Readers unfamiliar with text analysis are referred to Appendix A for a background to text analysis where the fundamental terminology and concepts are introduced.

To measure the political content of a text, both the Laver method and the random forest method rely on identifying words and phrases that separate different political positions from each other. The Udpipe package developed for R was used to analyze the speeches because it offers compatibility with the Swedish language to a greater extent than any other package found. The speech text was tokenized[1] by the language model trained from the Swedish speech database *"Svenska talbanken"*. Apart from splitting up the text of all speeches into tokens, it also

[1] Tokenization is the process of separating the full text into separate objects that can be used for numerical analysis. Examples of tokens are single words or phrases and symbols. See Appendix A for a more thorough explanation.

provides additional information on the tokens, such as token type (symbol, number, verb, noun, etc.) and its linguistic root (lemma)[2].

The selection of words and phrases was inspired by the methods used by Crawford and Levonyan (2018) and Gentzkow and Shapiro (2010). The set of single words were restricted to be nouns and was motivated by a need for dimension reduction and by an assumption that other word types in isolation are likely to hold little political information. Nouns on the other hand, I argue, are more likely to hold some political information since it essentially is what is talked about in the speeches. As in Crawford and Levonyan (2018) the most frequent words, in this case 5000, from left and right speeches were selected to be used in later analysis. Besides from including single words, also two-word phrases were considered. These were restricted to be noun phrases starting with an adjective, a verb or a noun and ending with a noun. As in the single word case, the 5000 most frequent phrases from both left and right speeches were selected to be used in later analysis. Three-word phrases were also considered at this step, but no extraction method was deemed good enough in selecting appropriate phrases. Merging the sets of words and phrases, the set contains a total of 5974 unique words and 6583 unique two-word phrases. At this point, following the approach in Gentzkow and Shapiro (2010), the chi-square test statistic was computed for all words and phrases. This step was implemented to select the words and phrases that are associated more with either left or right speeches. Left parties were defined as all those parties with a score between 0 and 5 from the survey of the population's perceptions of political parties, while all parties with a political score between 5 and 10 were defined as right parties. All words and phrases with a p-value of 0.01 or lower were retained in the set. The selection based on the chi-square test is a deviation from the approach used in Crawford and Levonyan (2018), who used all of the most frequent phrases by each political orientation without applying any method to select the words and phrases that separates the texts from different orientations the most. Since words and phrases that have a stronger association to either political side are likely to be better predictors of political bias, this approach seems like a reasonable addition to the Laver method. The last step of the selection process was to remove any procedural words and phrases and references to names of parties and party members. Procedural words and phrases were removed because they are unlikely to be used in other settings than in the parliament and follows the approach by both Gentzkow and Shapiro (2010) and Crawford and Levonyan (2018). The removal of references

[2] Lemma is the linguistic root of a word. The transformation to the linguistic root makes it possible to view words with the same meaning but in different forms as the same word. See Appendix A for a more thorough explanation.

to names and party names was done after inspection, showing that these references were more often used by the opposing side, indicating that they might not be used in the same way and context in the parliament as in other circumstances such as news.

The Laver method

In this section, the Laver method to measure the political leaning of words and phrases will be presented. The method identifies words and phrases in reference texts that are used more frequently and less frequently by each party and assigns a score to each word and phrase based on this relative usage. The reference texts should be texts with known political position and in this paper the collection of speeches from the left will be referred to as the reference text for the left and the collection of speeches from the right will be referred to as the reference text for the right. The Laver method is most likely to capture issue bias and to some degree also framing bias. Any results from this method should therefore be considered as either issue or framing bias.

The first step in the Laver method is to assign scores to words and phrases based on the relative usage in the reference texts. These scores of words are typically referred in the literature as slant scores, meaning that the words used in the reference texts have a political leaning. In calculating the slant score, the relative frequency, $F_{w,r}$ of each word or phrase (w) in a reference text (r) is calculated in all the left speeches $(F_{w,L})$ and right speeches $(F_{w,R})$ respectively. The relative frequency of a word or phrase is calculated as the frequency of that word or phrase, divided by the total frequency of words and phrases in the same reference document. These word and phrase specific relative frequencies are then used to calculate the probability of reading a text document of a specific political position, conditional on identifying a specific word or phrase in that document ($\mathrm{Pr}_{\mathrm{w,r}}$). An example of the calculation of this conditional probability is given in in Equation 4.1, where the probability of the document being left is calculated conditional upon that word w occurs in the document.

$$\mathrm{Pr}_{\mathrm{w,L}} = \frac{F_{w,L}}{\sum_r F_{w,r}}, \qquad \text{(Eq. 4.1)}$$

The conditional probability is computed for all words and phrases in all reference texts. To account for the political position (A) of each reference text, they are assigned a political position along the left-to-right dimension. In the final analysis of political slant, both a binary and a non-binary assignment will be used. In the binary assignment of political positions, all left speeches will be assigned +1 and all right speeches will be assigned -1. Instead, in the non-binary assignment, the collection of speeches from each party will be assigned the perceived political position presented in Table 3.2. The two different approaches are likely to give different views on any potential bias. In the binary assignment, the method will depict a clear left against right leaning, independent of the perceived political dimension of different parties. In the non-binary case instead, the political position of a party plays a greater part, because a similarity to one of the extremes will have a greater impact on the slant score of the text being analyzed.

The final slant score (political leaning of a word or phrase) is computed by summing the conditional probabilities multiplied with the political position of the reference texts. The equation for the final slant score of a word or phrase is presented in Equation 4.2.

$$S_{w,A} = \sum_r \Pr_{w,r} * A_r, \qquad \text{(Eq. 4.2)}$$

where $S_{w,d}$ is the slant score for word w on the political dimension A. The idea behind this method is that words and phrases are used relatively more frequently by either side because they are related to their political position and thus the relative use of these should capture the strength of this political information. If true, this could be used to measure the political position of a text or a collection of texts. The distribution of slant scores in the binary approach for all the selected words and phrases is presented in Figure 4.2. The histogram shows how many words and phrases fall into each bin of slant scores, where all negative slant scores show a leaning of usage to the right and all positive slant scores shows a leaning of usage to the left.

Figure 4.2: Counts of different slant scores for the full set of words and phrases

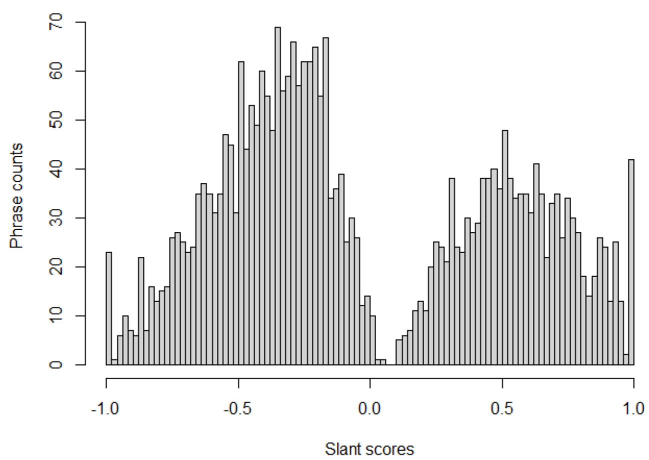
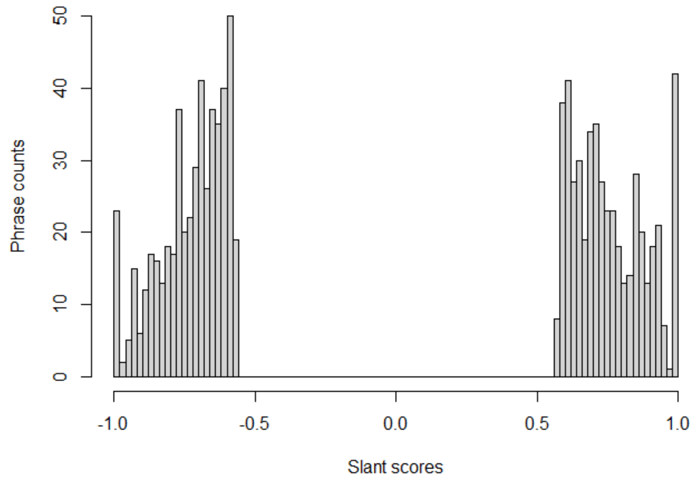


Figure 4.2 shows that words and phrases used more frequently by right parties were selected in the selection process to a greater extent than words and phrases used by left parties. In an attempt to balance the distribution of words and phrases, only the 500 rightmost and the 500 leftmost words and phrases were used in another calculation of slant scores. This set of slant scores of words and phrases will from now on be referred to as the 1st set. The distribution of slant scores in the 1st set is presented in Figure 4.3 and is more balanced than in Figure 4.2.

Figure 4.3: Counts of different slant scores for the 1st set

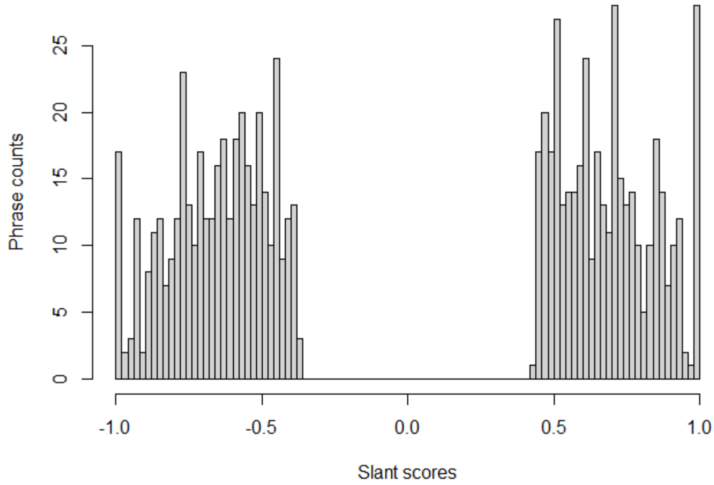


Later in the analysis, it will be shown that many of the words and phrases in the 1st set tend to be of non-political character. Thus a 2nd set of words and phrases were created after a manual removal of subjectively unpolitical terms[3], such as "Sports"[4]. This time, the 400 rightmost and 400 leftmost words and phrases were selected. The lower number of terms from each side was chosen because the total number of words and phrases decrease to 1022 and the left terms did not amount to 500. This set of slant scores will from now on be referred to as the 2nd set. Figure 4.4 presents the histogram of slant scores in the 2nd set and shows a similar separation of right and left phrases as in the 1st set.

[3] Subjectively unpolitical terms refer to words and phrases that were considered politically irrelevant from the authors own perspective.

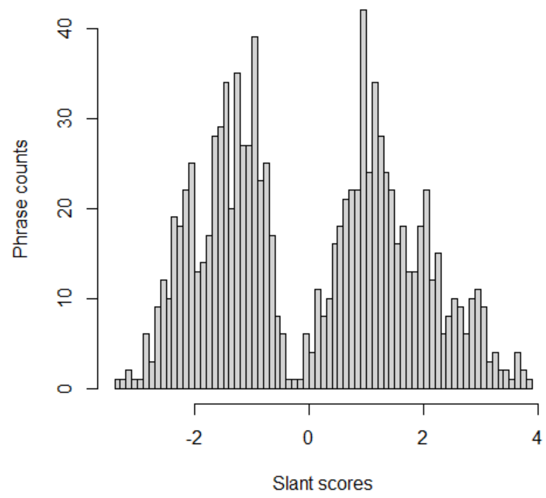
[4] Examples of words and phrases that were manually removed can be found in Appendix B Table B2. The words and phrases in the 1st set but not in the 2nd set are examples that were removed in this process.

Figure 4.4: Counts of different slant scores for the 2nd set



The last set of words and phrases on which slant scores was calculated is based on the non-binary assignment of political positions. Previously, all slanted words from the left parties were valued the same, but in this setting also the political position of the party who uses it more frequently will be taken into consideration. For example, a word used more by a Vänsterpartiet (the leftmost party) will be assigned a higher slant score than a word used to the same extent by Socialdemokraterna (the leftleast of the the left parties). All words and phrases retained after the manual removal was used in this set, since it no longer makes sense to exclude the words and phrases with a lower slant score. Excluding the lowest slant scores in this approach, could in theory exclude all words and phrases used by the parties closer to the center of the left-to-right political dimension. The distribution of slant scores in the 3rd set is presented in Figure 4.5. The distribution seems to be skewed to the left, with more of the left-slanted words and phrases being assigned a higher score than the right-slanted words and phrases. Note that the slant scores are considerably higher in the 3rd set compared to the 1st and the 2nd set. This is a consequence of the change in the definition of the left-to-right dimension, now ranging from -5 to +5 instead of between -1 and +1.

Figure 4.5: Counts of different slant scores for the 3rd set:



So far only texts of known political position have been used. Now the calculated slant scores based on these texts can be applied to new texts to measure if there is any leaning towards the left or the right. The aggregate slant of a new text in the Laver method is calculated by taking the sum of the relative frequencies of each word and phrase in the new text multiplied with their associated slant scores calculated from the reference texts, see Equation 4.3.

$$S_{v,A} = \sum_w F_{w,v} * S_{w,A}, \qquad \text{(Eq. 4.3)}$$

where $S_{v,A}$ is the calculated aggregate slant in the new text on the political dimension A. In this measure the slant could be viewed as the residual slant after summing the positive values for left leaning words and phrases with the negative values for the right leaning words and phrases.

Laver et al (2003) also presents a way of calculating the uncertainty of the calculated slant scores in the form of standard errors. First, the variance of the slant score is calculated by summing all of the squared differences between the score for each word and phrase in the new texts with its associated slant score from the reference texts, see Equation 4.4.

$$V_{v,A} = \sum_w F_{w,v}\left(S_{w,A} - S_{v,w,A}\right)^2, \qquad \text{(Eq. 4.4)}$$

where $V_{v,A}$ is the variance and $S_{v,w,A}$ is the contribution of slant of a single word or phrase in the new text (not to be confused with $S_{v,A}$ which is the aggregate slant of the new text). From the variance, the standard deviation is calculated by taking the square root. The standard error can then be computed by dividing the variance with the number of scored words in the text document for which the slant was calculated and taking the square root (Eq. 4.5). From this standard error, statistical tests can be performed and confidence intervals can be computed for statistical inference.

$$SE_{v,A} = \sqrt{\frac{V_{v,A}}{N_v}}, \qquad \text{(Eq. 4.5)}$$

The random forest method

This section will present how the random forest models were built and test the performance on training and test data. As in the section on the selection of words and phrases, readers not familiar with the random forest methodology is referred to Appendix A where an introduction to classification and random forest is presented.

The idea of using a machine learning algorithm to estimate political bias is to take the comparison approach, introduced above and in the literature review, one step further. In essence, the idea is to ask whether a news article is similar in total to a political speech from a specific party or not. At least two different alternatives for classification of this kind could be used. The first option is to use a binary model where the speech comes from either left or right parties. The other is to use binary models for each party and at a later stage aggregate the results from these models to be left, right or neither. If the purpose of the model would be to just classify speeches coming from the parliament, the first option is probably the best choice. In this case, some of the documents are likely to be completely apolitical. In such a scenario, the multiple binary models offer a great advantage in that they are not forced to classify all texts to any political orientation. Another advantage is that some texts might be similar to several parties, and in this way of classifying, the texts can be assigned to more than one party. Thus, the multiple binary model option was chosen. The possible advantage over the Laver method and similar methods used in previous literature is that it also considers combinations of words and phrases contained in the same text when assigning a text to a specific political position.

Six binary models for each party were built with different values for number of trees[5], number of words and phrases to consider at each node split and the minimum number of observations in each node. In order to choose which model to use in later analysis, the performance of these models was evaluated on the training data. The most straightforward measure of performance is the overall accuracy measured as the share of correctly classified observations out of the total

[5] Number of trees refers to the number of random forest classification trees that are built and combined in the random forest classification model to classify a text. See Appendix A for a more thorough explanation on random forest.

number of observations. Although, in some cases the overall accuracy might not be the best measure of performance. In a binary outcome setting for example, if the class of interest is very rare, the overall accuracy of the model could be almost 100 percent by just classifying all observations as the dominant class. In these cases, other measures like the sensitivity and the false positive rate (FPR) might be more interesting. Sensitivity is the measure of accuracy conditional on the observation belonging to a certain class (in our case being the specific party of interest). False positive rate is the measure of accuracy conditional on classifying the observation to a certain class when it should not be that class. All three measures will be presented when evaluating the performances of the party specific models, but a greater importance will be given to the FPR, since a high FPR would result in more speeches being classified as coming from a party when it is not. This could cause problems in the later classification of articles, resulting in a potential overestimation of political bias.

The parameter values used for each model is shown in Table 4.3. The performance of the different models for each party are presented in Tables 4.4a-c. In Table 4.4a the overall accuracy levels are increasing across all parties until model 5 and 6, with no substantial difference in overall accuracy between these two models. A similar pattern can be seen in both Table 4.3b for the FPR and in Table 4.3c for the sensitivity measure. Model 5 was chosen as the model to use in later estimations because it was built using more trees with other parameters identical to the ones in model 6.

Table 4.3: Parameter values of each model.

Parameter	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
ntrees	100	100	1,000	1,000	1,000	100
mtry	28	28	28	28	10	10
nodesize	1	10	10	1	1	1

Table 4.4a: Overall accuracy levels

Party	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
(V)	0.7427929	0.7537183	0.7436192	0.7524789	0.7711164	0.7651487
(MP)	0.6839423	0.6831620	0.6830242	0.6837587	0.7741003	0.7718050
(S)	0.7386614	0.7403140	0.7379269	0.7387532	0.7590892	0.7589056
(C)	0.6412046	0.6434080	0.6104021	0.6368436	0.7261752	0.7445832
(L)	0.6560779	0.6486412	0.6520841	0.6521759	0.7734576	0.7780481
(M)	0.6450147	0.6444638	0.6444638	0.6446015	0.7464653	0.7380646
(KD)	0.6771025	0.6737514	0.6737514	0.6732923	0.7129086	0.7135512
(SD)	0.6927562	0.6865130	0.6910577	0.6893592	0.7694179	0.7701065

Table 4.4b: False positivity rate

Party	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
(V)	0.7428367	0.7352941	0.7419633	0.7362164	0.7215918	0.7255633
(MP)	0.7789916	0.7784410	0.7784538	0.7780301	0.7303467	0.7327997
(S)	0.4498266	0.4477596	0.4508016	0.4497849	0.4102564	0.4101904
(C)	0.8548423	0.8543744	0.8705495	0.8557446	0.8356206	0.8292683
(L)	0.8750299	0.8771415	0.8763180	0.8753102	0.8450233	0.8435180
(M)	0.8423889	0.8426009	0.8425241	0.8424711	0.8115988	0.8159814
(KD)	0.6492030	0.6510229	0.6508413	0.6508586	0.6282219	0.6273904
(SD)	0.7745736	0.7774702	0.7753234	0.7758642	0.7353583	0.7346904

Table 4.4: Sensitivity

Party	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
(V)	0.8111161	0.8011749	0.8124718	0.8020786	0.7871667	0.7980117
(MP)	0.8229772	0.8296826	0.8301296	0.8301296	0.7022798	0.7013858
(S)	0.7876053	0.7879061	0.7883574	0.7886582	0.6919374	0.6895307
(C)	0.8513871	0.8487450	0.8044914	0.8566711	0.7199472	0.6935271
(L)	0.8515498	0.8539967	0.8515498	0.8605220	0.6794454	0.6704731
(M)	0.8597673	0.8597673	0.8603797	0.8603797	0.7201470	0.7262707
(KD)	0.8437118	0.8498168	0.8512821	0.8539683	0.7643468	0.7660562
(SD)	0.8282236	0.8336339	0.8300271	0.8331830	0.7110009	0.7110009

Another popular way of illustrating the performance of a classification model is to construct a confusion matrix. It shows the number of correctly classified observations in its diagonal elements and misclassifications on the off-diagonal elements. It makes it possible to understand what errors the classification model is making. Table 4.5 shows the confusion matrix for the model 5 binary models with the classifications in the columns and the actual party affiliation in the rows. For example, the intersection between the *MP* row and the *S* column represents the number of speeches that actually belong to *MP* but that were classified as *S* speeches. In this matrix a substantial number of speeches are misclassified, meaning it was classified as belonging to the wrong party. This can be seen from the high number of observations in the off-diagonal elements.

Table 4.5: Confusion matrix of all the binary models:

	No party	MP	S	SD	M	V	C	KD	L
No party	0	0	0	0	0	0	0	0	0
MP	27	693	818	587	841	679	594	655	490
S	94	1768	2570	1708	2500	1970	1859	1900	1536
SD	27	576	799	656	824	631	602	639	539
M	46	1067	1332	1161	1692	1163	1260	1243	1074
V	38	625	780	611	825	692	579	640	528
C	29	377	513	409	617	460	436	444	352
KD	22	438	543	445	618	486	466	527	408
L	16	328	417	367	502	354	354	397	326

The performance of the binary models is not a big concern if the aggregated performance on left and right speeches is high. In the aggregate classification between left and right, all the classifications from the party-specific binary models are combined. All speeches only classified as belonging to be either left or right are retained and classified as that. All speeches classified by the models to be both left and right are considered indetermined and not assigned to any side. Both the confusion matrix and the performance measures of the aggregated model is presented in Table 4.6.

Table 4.6: Confusion matrix and performance of aggregate model on training data:

	No party	Left	Right
No party	0	0	0
Left	3	3,970	1,202
Right	6	439	5,704

	Left	Right
FPR	0.09956906	0.1740515
Sensitivity	0.35772211	0.5337825

In the aggregated model, the performance measures are substantially better. The FPR measure is down to 10 percent on the left speeches and seventeen percent on the right speeches. The sensitivity measure drops and is down to 35 percent and 53 percent respectively.

The data used in the above evaluations was the training data. The performance based on the training data might be overestimated due to problems with overfitting, a common problem with many machine learning algorithms. That is why the same evaluation was done on the chosen models (model 5) using the test data, which were not used in the model building process. Table 4.7 presents the performance measures on the test data and shows a great decrease in performance. The FPR increases for both left and right speeches and for the right speeches it is even higher than 50 percent, meaning that over half of the speeches classified as right speeches were actually left speeches. The sensitivity measure also decreases to a very low level of 29 percent and 12 percent respectively. Evaluation of the performance of this classification model on the test data shows that it is a very poor model to classify the political affiliation of a speech. This also means that it would be highly problematic to use the model to estimate any political position of a news article based on this model. The random forest model built and chosen in this paper is thus deemed inappropriate and will not be used in any forthcoming analysis of bias in news reporting.

Table 4.7: Confusion matrix and performance of aggregate model on test data:

	No party	Left	Right
No party	0	0	0
Left	675	917	460
Right	1,223	660	352

	Left	Right
FPR	0.4185162	0.5665025
Sensitivity	0.2887280	0.1165949

5. Results

In this chapter, the results will be presented and discussed. First, the calculations of aggregate slant using the Laver method with the three sets of slant scores will be presented and discussed. Then the relationship between bias and voter preferences will be presented and discussed. The chapter ends with sensitivity analyses of the Laver method.

Calculations of aggregate slant with the Laver method

Public service slant scores (2016-2021)

In the study of political slant in public service, the SVT dataset was used. The aggregate slant throughout all periods using the Laver method (Eq. 3.3) with the 1st sets of slant scores is presented in Figure 5.1a. The aggregate slant is negative (slanted to the right) throughout all the studied time periods. Confidence intervals show that this slant to the right is significant until period 39 and insignificant in some periods after this. The aggregate slant for the full sample is presented in Figure 5.1b and is also significant to the right. One possible explanation for the sudden change towards the left (although still right in the calculated slant) could be the change in news content in the beginning of the covid pandemic. It is possible that the news coverage of the pandemic crowded out dominant right-leaning issues such as immigration and crime, leading to the aggregate slant moving in a left-ward direction. This would be in line with the importance of issue coverage found in Eisensee and Strömbäck (2007) discussed in the literature review.

Figure 5.1a: Aggregate slant for SVT in each period between 2016 and 2021 (1st set)

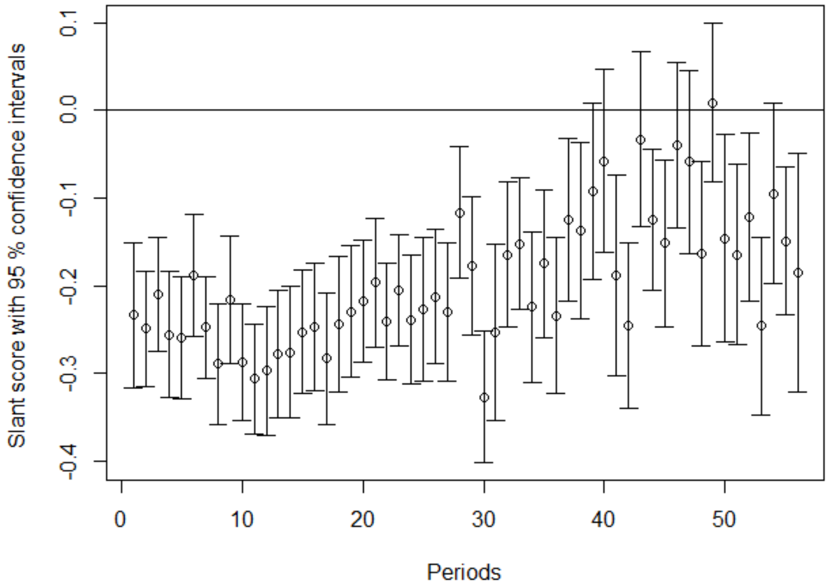
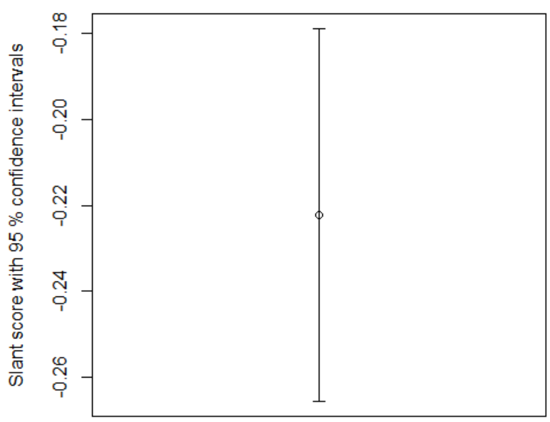


Figure 5.1b: Aggregate slant for SVT in all periods between 2016 and 2021 (1st set)



As mentioned earlier, many of the words and phrases used in this set are unlikely to be any good indicators of political position. An example of this is the word *sport* (*sports*) which contributes substantially to the aggregate slant to the right. This word is probably a problematic word to use for calculating slant in news reporting since *sports* are one of the largest topic categories in newspapers, independent of any political content. A list of the top 25 words and phrases that contributes the most to the left and to the right in the aggregate slant of the full sample is provided in Table B2 in Appendix B.

To solve this problem, the 2nd set of slant scores containing only politically relevant words was used to re-calculate the aggregate slant. Figure 5.2a presents the aggregate slant in all periods and Figure 5.2b presents the aggregate slant throughout all periods using this set of slant scores. The main picture of bias in public service news reporting remains also after the manual removal of subjectively unpolitical words and phrases but are no longer significant in most periods. The right bias is smaller in these estimations and significant only in a few periods. In some periods, the slant even shifts to the left. The aggregate slant for the full sample is still calculated to be significantly right. The reader is referred to Appendix B for Table B2 of the top 25 contributions in the aggregate slant on the full sample.

Figure 5.2a: Aggregate slant for SVT in each period between 2016 and 2021 (2nd set)

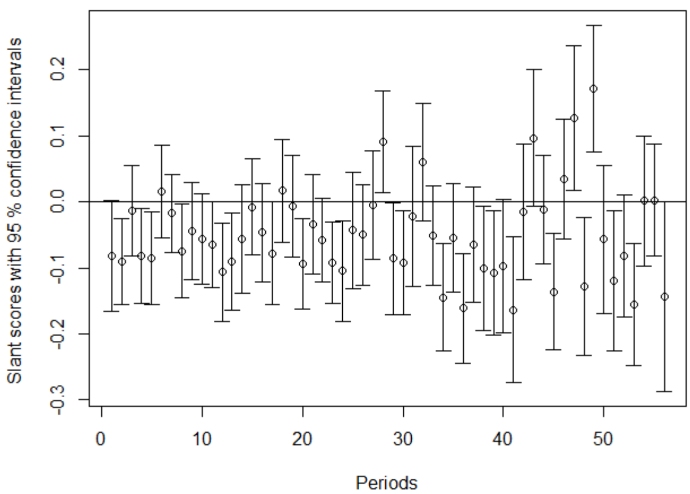
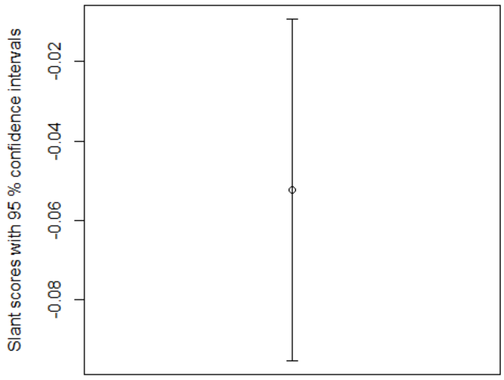


Figure 5.2b: Aggregate slant for SVT in all periods between 2016 and 2021 (2^{nd} set)



In the last calculations of aggregate slant on the SVT dataset, the third set of slant scores was used. As described in Chapter 4, these slant scores were calculated using a non-binary left-to-right dimension. The slant score assigned to each word and phrase in this setting also considers the exact political position of the party which used it more frequently and not only if the party is left or right. Figure 5.3a presents the aggregate slant in each period and Figure 5.3b presents the aggregate slant throughout all periods using this set of slant scores. The aggregate slant is calculated to be right and significant in most periods, as well as in the full sample. The general shift towards the right in this set is not surprising, as the right parties in general are further away from the center in their political positions (see Table 3.2), which should increase the slant scores to the right using the non-binary left-to-right dimension. Again, the top 25 contributors to each side can be found in Table B2 in Appendix B.

Figure 5.3a: Aggregate slant for SVT in each period between 2016 and 2021 (3rd set)

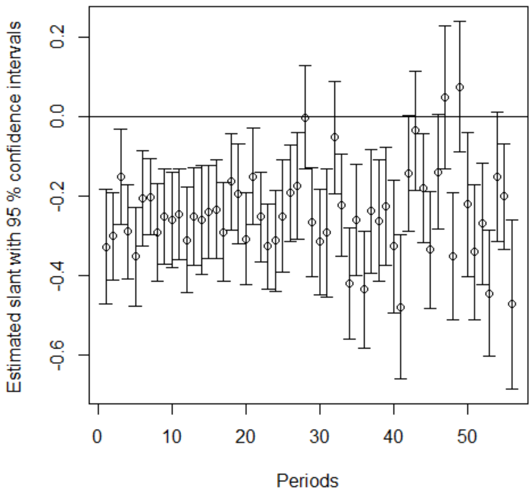
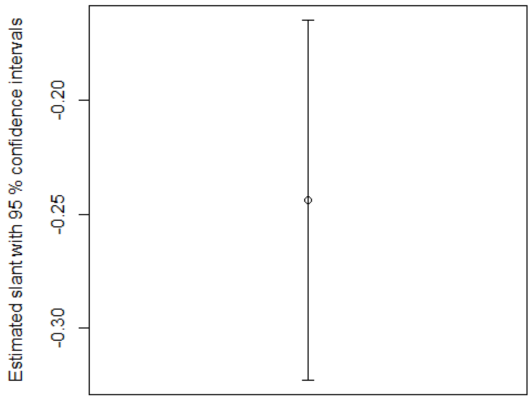


Figure 5.3b: Aggregate slant for SVT in all periods between 2016 and 2021 (3rd set)



In all of the calculations of aggregate slant, the news reporting of public service (SVT) is to the right. Additionally, using both the 1st and the 3rd set of slant scores, the aggregate right slant is significant in most of the studied periods and significant to the right on all sets on the full sample. These results suggest an overall bias towards the right in the public service news reporting by SVT. No consistent evidence supporting the claim of a left-leaning bias can be found using the Laver method. Even though, a left bias can be found in some periods. This is a contrasting result in many ways. It is contrary to the general belief and perception that the public service is left leaning. It is also contrary to the results on public service in the British public service found in Levonyan and Crawford (2018). In relation to theory, it might be surprising as well. The main source of a potential bias in public service should be the preferences by the employees (see theoretical framework), but since the political preferences of the employees are to the left, also the bias should be to the left. Even in a setting where the ownership's preferences are considered, economic theory cannot explain the right leaning bias found, since the government during this period has been led by left parties. One possible explanation for the results have more to do with methodology than theory. Total bias in news reporting can come from many different types of biases and the Laver method is more likely to capture issue bias than other types. It is possible that the issues being covered in the studied time has had a strong right bias, but that the way they were commented or the facts presented together with them were left leaning. This would result in a right leaning issue bias, but a left leaning in other types of biases, which in total could dominate over the right leaning issue bias.

The relationship between political news bias and voter preferences

To analyze the relationship between voter preferences and political bias in the Swedish public service news reporting, the correlation of the change in opinion polls on voter preferences between periods and the change in political bias in the preceding period was computed. Both the aggregate slant calculated by using the 2nd and the 3rd set of slant scores were used. Figure 5.6 shows the time series of the change in voter preferences and change in aggregate slant in news reporting in the preceding period using the 2nd set, while Figure 5.7 shows the same time series using the 3rd set.

Figure 5.6: Changes in aggregate slant and changes in voter preferences between (2nd set)

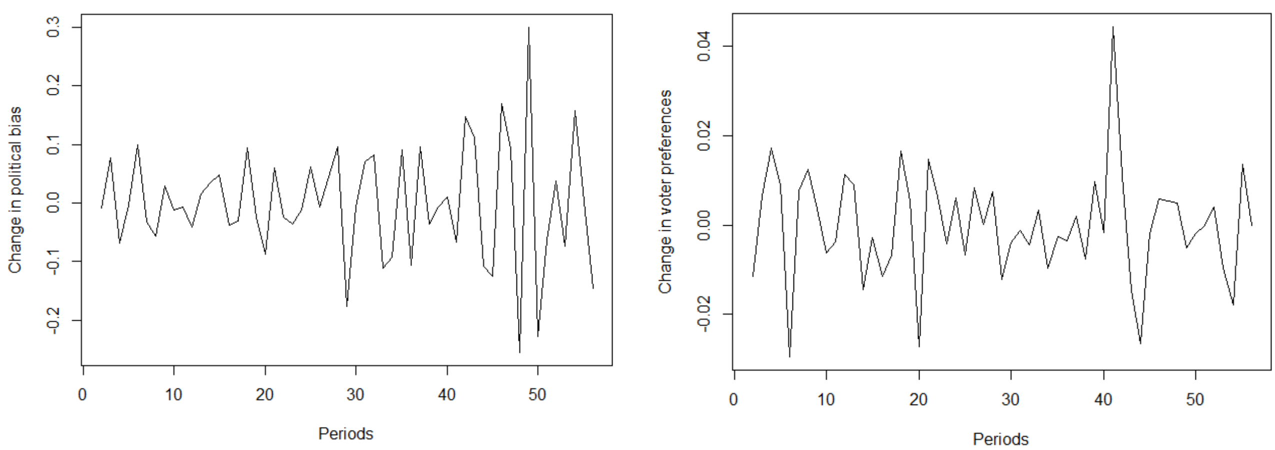
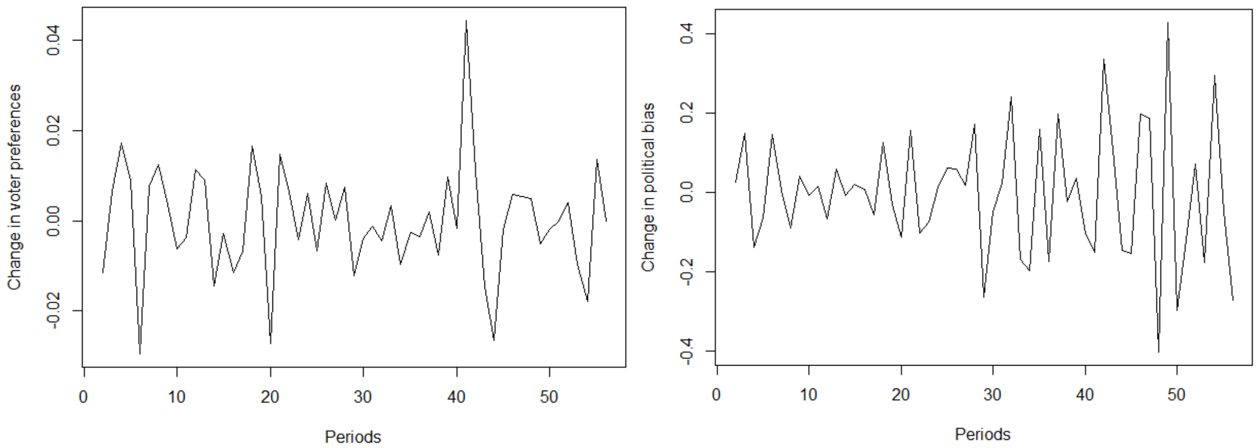


Figure 5.7: Changes in voter preferences and changes in political bias (3rd set)



No obvious relationship between the change in aggregate slant and the change in voter preferences can be seen in any of the figures. A more formal analysis of this relationship was done by calculating the correlation between the change in voter preferences and the change in aggregate slant in the preceding period and is shown in Table 5.9. In both cases, the correlation between the change in aggregate slant and voter preferences is weak and shows no support of a strong relationship between these two variables. The results are indicative at best, but if true, it would mean that political bias in public service news reporting is not as important for voter preferences as one might think. Worth noting is also that this analysis only included the calculated bias in the public service, whereas an analysis including a larger share of the media market might give different results.

Table 5.9: Correlations of change in slant and change in voter preferences.

	Correlation
2nd set	0.008
3rd set	0.003

Sensitivity analysis

In this section, sensitivity analyses of the Laver method using the 2nd and the 3rd set of slant scores will be presented. First, the aggregate slant of commercial news outlets will be calculated using the 2nd set to see if it positions them according to their perceived political position on the left-to-right dimension. Second, the changes in aggregate slant of different news outlets will be analysed to see if news outlets seem to follow a similar slant trend in their news reporting. Third, the test data on political speeches will be used to see how well the Laver method performs in positioning these speeches relative to their actual political positions.

Slant scores across news outlets

In the analysis of aggregate slant across news outlets, the dataset of September 2020 to September 2021 was used. The same slant scores as in the 2nd set (binary approach) was used to calculate the aggregate slant in all commercial news outlets. The resulting aggregate slant for each news outlet in each period is presented in Figure 5.4. The aggregate slant for SVT is significantly left in two periods and significantly right in three periods. The aggregate slant for Aftonbladet (AB) is significantly left in four periods and right in none, in line with the perceived left position of Aftonbladet. Svenska Dagbladet (SvD) is significantly left in one period and significantly right in none of the periods, somewhat in contrast to the perceived right political position. The estimates for Dagens Nyheter (DN) are significantly left in four periods, also in contrast with the perceived right political position.

Figure 5.4: Aggregate slant for all news outlets in each period between 2020 and 2021

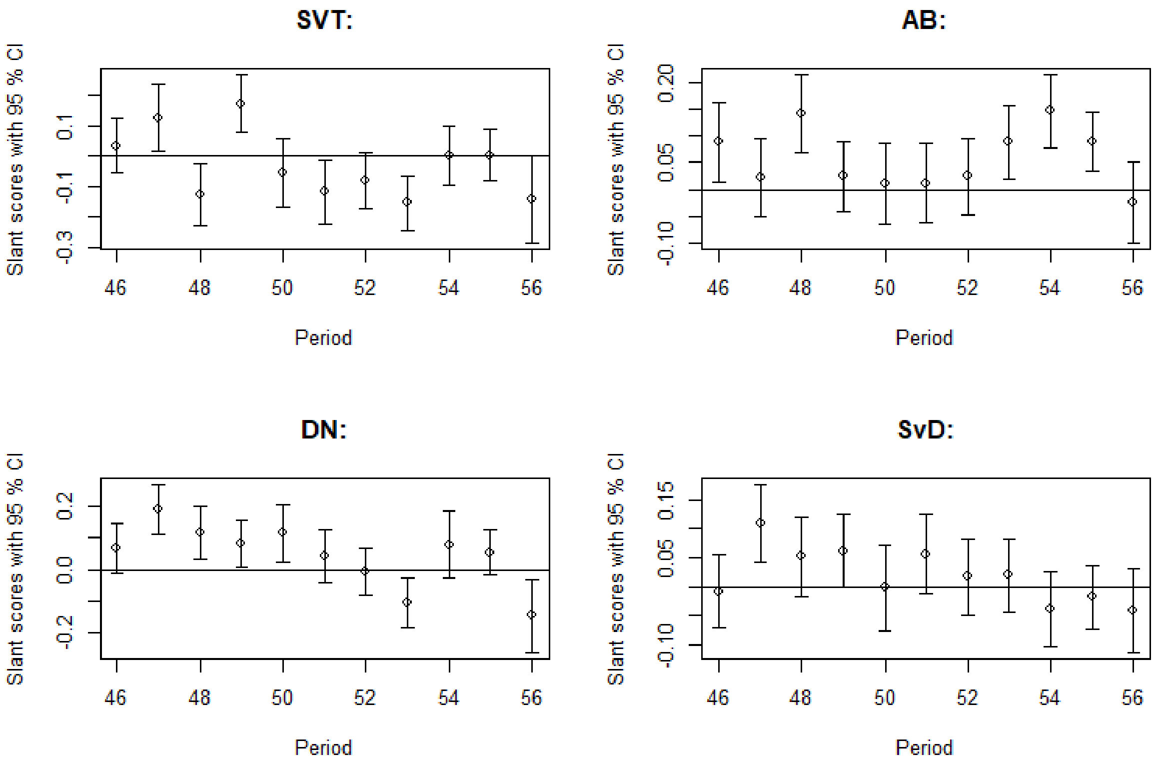
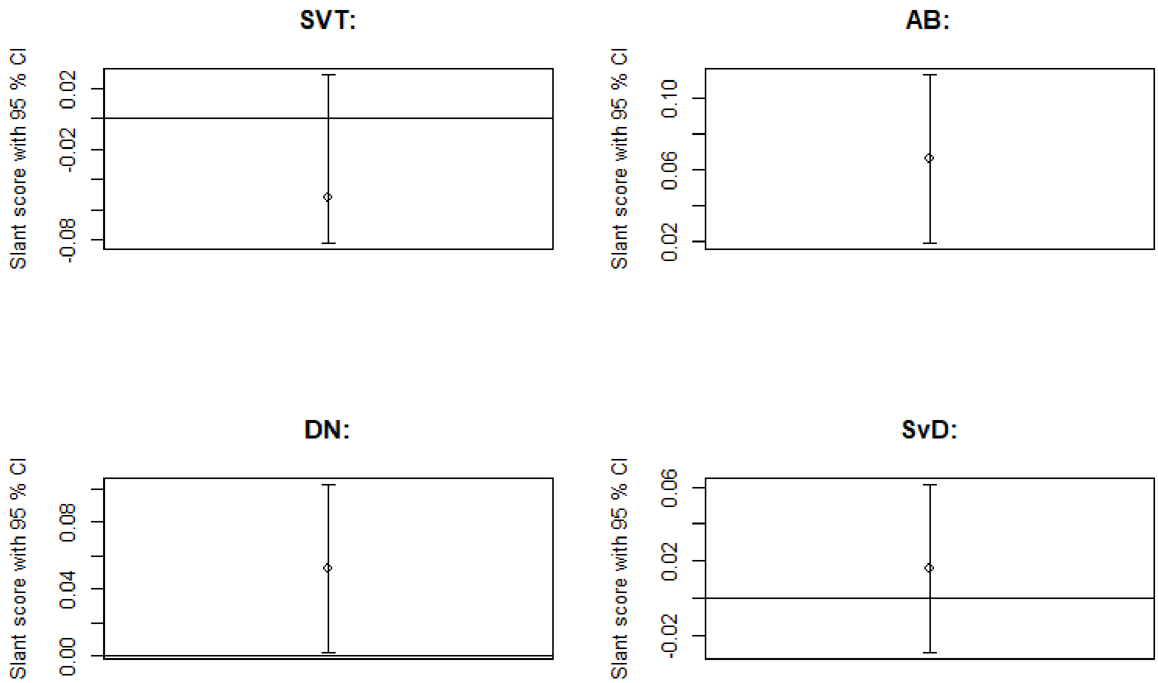


Figure 5.5 presents the aggregate slant for the full parliamentary year of 2020-2021. The SVT slant suggest a significant leaning to the right also in this specific year, while the slant of both Aftonbladet and Dagens Nyheter are significant to the left. The slant of Svenska Dagbladet is left but not significant. All in all, the aggregate slant of the three commercial news outlets seem to place them in a correct order in relative terms compared to their perceived political positions, with Aftonbladet most to the left and Svenska Dagbladet most to the right. This is an indication that at least the placing of news outlets´ political positioning is reasonable. All of them are placed to the left though, which might indicate that the words and phrases considered might bias the aggregate slant towards the left. This finding makes the right slant found in SVT even more interesting, since it might indicate that the Laver method in this case underestimates any bias to the right.

Figure 5.5: Aggregate slant for all news outlets between 2020-2021 (2^{nd} set)



To see if the development of political bias in different news outlets seem to follow a similar trend, correlations between the changes in aggregate slant between periods were computed across all news outlets. Correlations close to one would mean that the slant is developing almost the same across news outlets, indicating that the development of any slant is mostly driven by trends in news that affect news outlets to report similar news. For example, an important political statement from a specific party which gain exposure in the news reporting in all news outlets. The development of slant across news outlets is presented in Figure 5.6. No clear pattern in the development of slant can be seen in the graph across news outlets.

Figure 5.6: Development of bias across news outlets in 2020-2021:

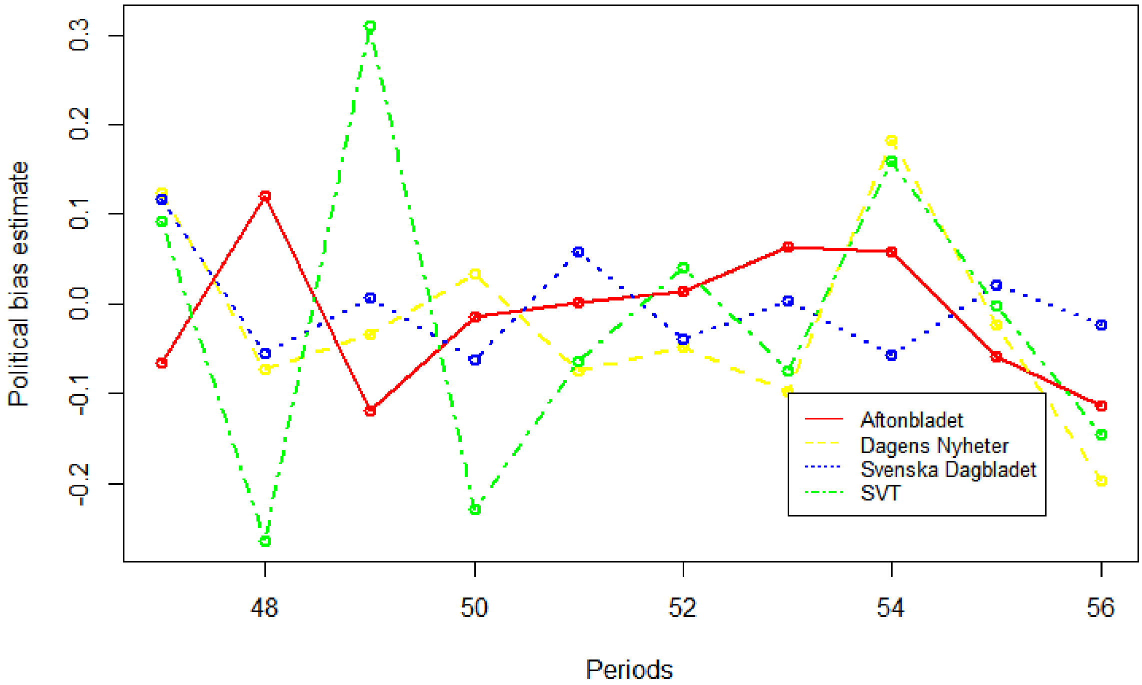


Table 5.4 formalize this analysis in the form of a correlation matrix across news outlets. The correlation matrix shows no clear evidence for a similar development of bias between the different news outlets. Some outlets seem to correlate fairly well, like SVT and DN with a correlation of 0,44. But overall, the correlations are weak and, in many cases, even negative. The weak and or negative correlation is to be expected if the bias in news reporting is affected more by the preferences of consumers, owners or editors and journalists, rather than the issues most newsworthy to the population at the time. This suggests that any bias that the method capture is at least not dominated by a trend of news towards certain issues and that any potential bias found is likely to be driven by either demand or supply factors.

Table 5.4: Correlations matrix of development of bias across news outlets

	Aftonbladet	Dagens Nyheter	Svenska Dagbladet	SVT
Aftonbladet	1.000	0.148	-0.414	-0.413
Dagens Nyheter	0.148	1.000	0.110	0.443
Svenska Dagbladet	-0.414	0.109	1.000	0.326
SVT	-0.413	0.443	0.326	1.000

Slant scores on speeches in the test set

Another way of evaluating how well the Laver method scores possibly slanted texts is to use the test data that was not part of the data used to compute the slant scores for the words and phrases. Both the 2nd and the 3rd set of slant scores was used on this data to see how it assigned aggregate slants to speeches in the full sample, the left, the right and all individual parties. Table 5.5 presents the aggregate slant on these speeches.

Table 5.5: Aggregate slant on test data

	All	Left	Right	(V)	(MP)	(S)	(C)	(L)	(KD)	(M)	(SD)
2nd set	-0.042	-0.030	-0.055	-0.056	-0.065	-0.013	-0.049	-0.029	-0.054	-0.071	-0.039
3rd set	-0.152	-0.142	-0.163	-0.189	-0.190	-0.115	-0.164	-0.145	-0.169	-0.174	-0.146

Table 5.5 shows a severe right bias in the aggregate slants. All the party speeches have aggregate slants that are negative, both in the calculations using the 2nd and the 3rd set. Especially problematic for the validity of the method is the right leaning slant of the left parties and that in the 2nd set, the speeches by the leftmost parties in the parliament are assigned the highest right leaning slants. Since the methods don't perform well on assigning the political position of the political speeches, it is unlikely that it performs well on the article texts.

Many possible explanations for the lack of performance exist. One is that the selection process of words and phrases was too small or that the selected words and phrases weren't the most informative in political leaning among all the possible words and phrases in the political speeches. However, this problem should have been alleviated by the manual removal of politically irrelevant words and phrases and thus it seems like an unlikely main cause of the poor performance. Another plausible explanation is that a large share of the speeches that were used to calculate the slant scores (Laver method) and also to build the classification models (random forest method), was lacking in political content. If this would be the case, it could explain the poor performance, since the words and phrases would be chosen also based on these less informative speeches. A third possible explanation has to do with the time frame in which all words and phrases were assigned a slant. In this paper, the slant scores were calculated on the whole dataset, and the political slant of each word and phrase was thus assumed to be constant during this time. This might introduce a problem if left or right parties have changed their usage of words and phrases within the studied period, perhaps as a consequence of a change in suggested policies. An important example of this is the dominant left party, Socialdemokraterna, who changed its rhetoric and policies on immigration and became more aligned with the right parties during this time.

6. Conclusions

In this paper, political bias in public service in the Swedish public service (SVT) has been studied. The calculations of political slant suggest a significant right bias in the news reporting by SVT in all of the different set of slant scores, contrary to the public perception of the public service as left leaning. Further analysis into the reliability of the method used shows that these aggregated slants are likely to be misleading. When the same method was applied to speeches set aside for evaluation of the method, even the leftmost party was calculated to have a right leaning political slant. Even if the exact position on the left-to-right dimension calculated by the Laver method seems unreliable, the method still seems to place commercial news outlets in accordance with the perceived political positions. This result indicates that the method is capable of placing news reporting from different news outlets in a proper way. Interestingly, SVT is placed most to the right among all the studied news outlets, more to the right than the rightmost news outlet Svenska Dagbladet. This result again suggests that, opposite to popular perceptions, SVT is not politically biased to the left but rather to the right. Although, due to the low performance of placing political parties on the left-to-right dimension, this would need to be analyzed using a more robust method before any final conclusions can be drawn.

In future research, it would probably be beneficial to refine the selection process of words and phrases, to see if this might yield better performance. I would also recommend working with shorter time spans when assigning slant scores to words and phrases to minimize the problem of political parties changing their usage of these as discussed above. Doing the analysis on an annual basis would probably be a good choice. In future research it would also be interesting to see how adding sentiment analysis might affect the calculated bias, in other words, to account for the sentiment (positive, negative or neutral) in which a word or phrase is used.

References

Asp, K. (Red.). (2012). *Svenska journalister 1989-2011*. Institutionen för journalistik, medier och kommunikation, Gothenburg University.

Ansolabehere, S., Lessem, R., & Snyder, J. M. (2006). *The orientation of newspaper endorsements in US elections*,1940-2002. Quarterly Journal of Economics, Vol 1(4), p. 393-404. DOI: 10.1561/100.00000009

Butler, D. M., & Schofield, E. (2010). *Were Newspapers More Interested in Pro-Obama Letters to the Editor in 2008? Evidence From a Field Experiment*. American Politics Research, Vol 38(2), p. 356-371. DOI: 10.1177/1532673X09349912

DellaVigna, S., & Kaplan, E. (2007). *The Fox News Effect: Media Bias and Voting*. The Quarterly Journal of Economics, Vol 122(3), p. 1187-1234. DOI: 10.1162/qjec.122.3.1187

Eisensee, T., & Strömbäck, D. (2007). *News droughts, news floods, and US disaster relief*. The Quarterly Journal of Economics, Vol 122(2), p. 693-728. DOI: 10.1162/qjec.122.2.693

Encyclopædia Britannica. (2022). *Data mining*. 2022-06-06. https://www.britannica.com/technology/data-mining

Erikson, R. S. (1976). *The Influence of Newspaper Endorsements in Presidential Elections*. American Journal of Political Science, Vol 20(2), p. 207-233. DOI: 10.2307/2110642

Gentzkow, M., Kelly, B., & Taddy, M. (2019). *Text as Data*. Journal of Economic Literature, Vol 57(3), p. 535-574. American Economic Association. DOI: 10.1257/jel.20181020

Gentzkow, M., & Shapiro, J. M. (2010). *What Drives Media Slant? Evidence From U.S. Daily Newspapers*. Econometrica, Vol 78(1), p. 35-71. DOI: 10.3982/ECTA7195

Gerber, A. S., & Karlan, D. (2009). *Does the Media Matter? A Field Experiment Measuring the Effect of Newspapers on Voting Behavior and Political Opinions*. American Economic Journal: Applied Economics, Vol 1(2), p. 35-52. DOI: 10.1257/app.1.2.35

Groseclose, T., & Milyo, J. (2005). *A Measure of Media Bias*. The Quarterly Journal of Economics, Vol 120(4), p. 1191-1237. DOI: 10.1162/003355305775097542

Kahneman, D., & Tversky, A. (1984). *Choices, Values and Frames*. The American Psychologist, Vol 39(4), p. 341-350. DOI: 10.1037/0003-066X.39.4.341

Kantar Sifo. (2022). *VÄLJARBAROMETERN*. https://www.kantarsifo.se/rapporter-undersokningar/valjarbarometern

Kuhn, M., & Johnson K. (2013). *Applied Predictive Modeling*. Springer. DOI 10.1007/978-1-4614-6849-3

Laver, M., Benoit, K., & Garry, J. (2003). *Extracting Policy Positions from Political Texts Using Words as Data*. The American Political Science Review, Vol 97(2), p. 311-331. Cambridge University Press. DOI: 10.1017/S0003055403000698

McCombs, M. E., & Shaw, D. L. (1972). *THE AGENDA-SETTING FUNCTION OF MASS MEDIA*. Public Opinion Quarterly, Vol 36(2), p. 176-187. DOI: 10.1086/267990

Medieakademin. (2021). Förtroendebarometern 2021. https://medieakademin.se/wp-content/uploads/2021/03/Presentation_fortroendebarometern_2021-1.pdf

Myndigheten för press, radio och TV. (2022). *Det här är public service*. https://www.mprt.se/sanda-och-publicera-media/public-service/#:~:text=Public%20service%20%C3%A4r%20radio%20och,%C3%A4ven%20andra%20maktsf%C3%A4rer%20i%20samh%C3%A4llet.

Oscarsson, H. & Svensson, R. (2020). *Partiernas vänster-högerpositioner 1968-2019*. Valforskningsprogrammets rapportserie 2020:2. Gothenburg University.

Prat, A., & Strömbäck, D. (2013). *The Political Economy of Mass Media*. Acemoglu, D., Arellano, M., & Dekel, E. (Eds.). Advances in Economics and Econometrics: Tenth World Congress (Econometric Society Monographs). Cambridge University Press. DOI:10.1017/CBO9781139060028

Puglisi, R., & Snyder, J. M. (2015). *Empirical Studies of Media Bias*. Anderson, S. P., Waldfogel, J., & Strömberg, D. (Eds). Handbook of Media Economic, Vol 1, p. 647-667. Elsevier Science & Technology.

RetrieverGroup. (2021). *Mediearkivet*. 2022-06-06: https://www.retrievergroup.com/sv/product-mediearkivet)

Riksdagen. (2022). *Anföranden*. 2022-03-10 https://data.riksdagen.se/data/anforanden/

Siddiqi, S., & Sharan, A. (2015). *Keyword and Keyphrase Extraction Techniques: A Literature Review*. International Journal of Computer Applications, Vol 109(2), p. 18-23. DOI: 10.5120/19161-0607

Snyder, J. M., & Strömbäck, D. (2010). *Press Coverage and Political Accountability*. The Journal of Political Economy, Vol 118(2), p. 355-408. DOI: 10.1086/652903

Weiss, S. M., Indurkhya, N., & Zhang, T. (2010). *Fundamentals of Predictive Text Mining*. Springer. DOI: 10.1007/978-1-4471-6750-1

Appendices

Appendix A: Background to text mining and random forest

In this appendix the terminology and concepts used in this paper from text mining and random forest are presented. It is intended for those who have not seen any text mining applications or the use of random forest before.

What is text mining?

Data mining is defined within computer science as "*the process of discovering interesting and useful patterns and relationships in large volumes of data*" (Britannica, 2022). As the name text mining suggests, text mining is data mining applied to data in text format. The crucial difference in traditional data mining applications and text mining applications is in the raw format in which the data is attained. In traditional data mining applications, the data is already represented in a numerical format and besides structuring the data, there is often not much more to do before the learning process can begin. Instead with text, the data need first to be transformed somehow into numbers (Weiss et al, 2010). This additional step included in text mining will be covered below in the section Transforming text to numbers. After transforming the text to numerical data most of the techniques developed for traditional data mining can be used for text mining as well.

Transforming text to numbers

Many considerations and slightly different approaches exist on how to transform text data into numbers. In this section I will describe the approach set up by Weiss et al (2010) but generally the approaches are very similar. The first step is collecting the text documents and if necessary, standardize them into the same format. Once the text documents have been collected and standardized, the text is divided through a process called tokenization into tokens. Tokens are typically words, but other attributes like symbols and emoticons have also been used in text mining applications. This method is called *Bag of Words* and neglect information in the text related to grammar or the exact meaning of a word in its specific context. Neglecting this potential information in text might seem limiting but even in this setting, methods have been proven to yield successful results.

After tokenization, the text data is structured with at least two columns, one column identifying the document and the other identifying a token present in the document. A dataset containing thousands of text documents will contain a very large set of unique features (unique tokens) referred to as the dictionary. An optional step at this point is to use a lemmatizer, a function which transform features into their linguistic roots. As an example, this means that features like run, running, runs will all be transformed to the same linguistic root *run*. This step preserves the core meaning of each word, while decreasing the number of unique words to keep track of. In some cases, it also leads to a higher performance of later applied models. In some cases, also building additional features from the feature set can improve the final performance of a classification model (Siddiqi and Sharan, 2015). One common way of doing that is to consider phrases of two or three words and adding them to the feature set (See Gentzkow and Shapiro, 2010; Crawford and Levonyan, 2018).

In many applications the number of features will be very high which will result in estimation times that might not be feasible later. Gentzkow, Kelly and Taddy (2019) highlight that in most applications the full set of features (the dictionary) will be too big. They propose filtering out tokens which are likely to have low informational value for classification. Examples of this is to remove symbols and numbers. Another possible step to reduce the dictionary size is to remove very common words referred to as stop words.

For many applications of text mining these approaches are not enough to reduce the dimensionality to a manageable set of features. In these cases, feature selection can be used to select features which are more likely to hold high informational value. The simplest approach is to restrict the set of tokens only to those occurring within a specified range of frequency. Very low frequencies are not likely to pick up any systematic information about a document, while very high frequency will likely not discriminate enough between documents. Another approach to decrease dimensionality further is to select features based on their actual informational value. One common way of doing this is to rank the potential features according to their association with the outcome variable. This approach was used in Gentzkow and Shapiro (2010), where they used the Pearson’s chi square statistic of independence. The null hypothesis for this test is that the predictor and the outcome are independent. A low value supports the hypothesis of independence and predictors with the highest values are selected as predictors in the final model.

After the features have been selected, the actual transforming of data from text to numbers is done by structuring the text into a document term matrix (dtm). In this matrix every row represents one text document and every column represents a term (feature). An example is a dataset containing 100 text documents with a total number of 10,000 features. In this case the dtm would contain a total of one million cells, each cell representing the existence or frequency of a specific word in a specific document.

Random forest

Classification is one of the most widely used applications in text mining (Weiss et al, 2010). In text mining, classification can broadly be described as a method of assigning labels to a set of unlabelled documents by using information from a collection of documents with known labels. For the purposes of this paper, a model for classification called random forest will be used. It is an extension of regression trees but should not be confused with the more traditional regression approaches used in econometrics (Gentzkow, Kelly and Taddy, 2019). The simplest way of explaining the random forest method for classification is to start with an explanation of the regression tree. One of the oldest and commonly used regression tree approach is the classification and regression tree (CART. The approach in a regression tree is to search for a predictor in the data set which partition the dataset into two groups based on minimizing the sum of squared errors (SSE), in this case minimizing the error rate in prediction. Each split of the dataset in the tree is called a node and with each split a visual representation of the growing regression would look like the continuation of a tree branch. This procedure is then iterated in each partition of the sample until a stopping condition is met, usually restricting any partition to contain a certain number of observations. Classification of new samples is done by simply following the tree (set of conditions) down to one of these leaves. The approach gained popularity because it does not require any assumptions about the distribution of predictors or of their inherent relationship with the outcome variable. Other advantages compared to the traditional approaches is that feature selection is done automatically in the model (only predictors partitioning the sample in a sufficient way will be used) and because of its simple visual representation and interpretability of conditions leading to its predictions. These advantages aside, the approach suffers from model instability and unsatisfying predictive performance in many cases. Because of these weaknesses, many researchers developed the idea of single regression trees and extended it to an ensemble of trees. (Kuhn and Johnson, 2013). Random Forest is one of the most famous and widely used of these extensions and was popularized by Breiman (2001). In a random forest, multiple trees (often thousands) of regression trees are grown independently. Each tree is grown from a random draw with replacement of the full sample, known as *bagging*. Additionally, at each node split, random sampling with replacement from all possible predictors are considered and chosen based on its Gini index. The Gini index is a measure of the uncertainty of an event occurring or in the context of classification of which class the data belongs to. Equation 6 shows how it is calculated:

$$Gini(t) = 1 - \sum_{i=1}^{N} P(C_i|t)^2, \qquad \text{(Eq. 6)}$$

where t is the condition (occurrence of a word or phrase), N is the number of classes in the data set and C_i is the ith class label in the data set. (Fawagreh et al, 2014). The assignment of class in the classification of a random forest is then decided by a majority vote on which class the observations belong by all trees in the forest.

Appendix B: Additional tables and figures

Figure B1: Raw data on opinion polls from 2016-08-18 to 2021-09-16

Start period	End period	Date	S	V	MP	M	C	L	KD	SD	Left	Right
2	1	2016-09-15	0.280	0.076	0.042	0.248	0.084	0.052	0.030	0.156	**0.398**	**0.570**
3	2	2016-10-13	0.259	0.082	0.047	0.250	0.083	0.054	0.028	0.168	**0.388**	**0.583**
4	3	2016-11-17	0.275	0.075	0.044	0.231	0.087	0.065	0.035	0.158	**0.394**	**0.576**
5	4	2016-12-15	0.276	0.084	0.052	0.222	0.091	0.060	0.036	0.152	**0.412**	**0.561**
6	5	2017-01-19	0.297	0.080	0.043	0.219	0.093	0.053	0.026	0.160	**0.420**	**0.551**
7	6	2017-02-16	0.275	0.069	0.049	0.204	0.118	0.056	0.036	0.168	**0.393**	**0.582**
8	7	2017-03-16	0.287	0.071	0.045	0.184	0.142	0.057	0.028	0.167	**0.403**	**0.578**
9	8	2017-04-15	0.299	0.082	0.032	0.175	0.138	0.054	0.029	0.167	**0.413**	**0.563**
10	9	2017-05-11	0.295	0.078	0.037	0.175	0.126	0.057	0.027	0.166	**0.410**	**0.551**
11	10	2017-06-15	0.292	0.077	0.040	0.159	0.134	0.062	0.029	0.180	**0.409**	**0.564**
12	11	2017-08-17	0.300	0.064	0.041	0.162	0.124	0.062	0.036	0.183	**0.405**	**0.567**
13	12	2017-09-14	0.297	0.074	0.045	0.172	0.119	0.050	0.037	0.178	**0.416**	**0.556**
14	13	2017-10-12	0.305	0.083	0.038	0.186	0.123	0.061	0.029	0.150	**0.426**	**0.549**
15	14	2017-11-09	0.298	0.069	0.042	0.224	0.103	0.054	0.031	0.147	**0.409**	**0.559**
16	15	2017-12-14	0.293	0.074	0.041	0.220	0.102	0.050	0.027	0.165	**0.408**	**0.564**
17	16	2018-01-18	0.278	0.077	0.041	0.244	0.088	0.051	0.029	0.162	**0.396**	**0.574**
18	17	2018-02-15	0.273	0.072	0.046	0.238	0.105	0.050	0.028	0.162	**0.391**	**0.583**
19	18	2018-03-15	0.290	0.077	0.038	0.231	0.100	0.044	0.030	0.159	**0.405**	**0.564**
20	19	2018-04-12	0.284	0.081	0.041	0.230	0.097	0.044	0.034	0.148	**0.406**	**0.553**
21	20	2018-05-17	0.252	0.093	0.040	0.236	0.081	0.048	0.035	0.187	**0.385**	**0.587**
22	21	2018-06-14	0.261	0.098	0.040	0.206	0.108	0.049	0.024	0.185	**0.399**	**0.572**
23	22	2018-08-09	0.258	0.092	0.056	0.203	0.103	0.060	0.033	0.168	**0.406**	**0.567**
24	23	2018-09-09	0.283	0.080	0.044	0.198	0.086	0.055	0.063	0.175	**0.407**	**0.578**
25	24	2018-10-18	0.294	0.079	0.041	0.188	0.091	0.049	0.060	0.186	**0.414**	**0.574**
26	25	2018-11-15	0.290	0.076	0.041	0.181	0.090	0.049	0.067	0.193	**0.407**	**0.580**
27	26	2018-12-13	0.297	0.077	0.042	0.190	0.077	0.040	0.066	0.200	**0.416**	**0.573**
28	27	2019-01-17	0.293	0.085	0.039	0.195	0.069	0.036	0.075	0.199	**0.417**	**0.574**
29	28	2019-02-14	0.284	0.096	0.043	0.172	0.077	0.038	0.086	0.192	**0.423**	**0.565**

30	29	2019-03-14	0.274	0.098	0.038	0.175	0.083	0.033	0.094	0.191	**0.410**	**0.576**
31	30	2019-04-11	0.273	0.087	0.046	0.160	0.075	0.034	0.122	0.189	**0.406**	**0.580**
32	31	2019-05-16	0.270	0.089	0.045	0.159	0.082	0.038	0.120	0.181	**0.404**	**0.580**
33	32	2019-06-13	0.265	0.086	0.049	0.184	0.088	0.037	0.095	0.181	**0.400**	**0.585**
34	33	2019-08-15	0.268	0.087	0.049	0.191	0.088	0.038	0.084	0.182	**0.404**	**0.583**
35	34	2019-09-12	0.258	0.085	0.051	0.189	0.086	0.042	0.073	0.202	**0.394**	**0.592**
36	35	2019-10-17	0.249	0.092	0.050	0.177	0.084	0.039	0.067	0.227	**0.391**	**0.594**
37	36	2019-11-14	0.244	0.097	0.047	0.170	0.083	0.036	0.079	0.230	**0.388**	**0.598**
38	37	2019-12-12	0.246	0.097	0.047	0.172	0.080	0.040	0.060	0.244	**0.390**	**0.596**
39	38	2020-01-16	0.235	0.102	0.045	0.175	0.085	0.039	0.066	0.238	**0.382**	**0.603**
40	39	2020-02-13	0.236	0.114	0.042	0.175	0.081	0.044	0.061	0.233	**0.392**	**0.594**
41	40	2020-03-12	0.238	0.112	0.040	0.180	0.084	0.041	0.068	0.222	**0.390**	**0.595**
42	41	2020-04-08	0.306	0.094	0.035	0.192	0.069	0.038	0.059	0.195	**0.435**	**0.553**
43	42	2020-05-14	0.317	0.090	0.039	0.186	0.072	0.034	0.061	0.189	**0.446**	**0.542**
44	43	2020-06-11	0.300	0.096	0.035	0.195	0.070	0.034	0.068	0.189	**0.431**	**0.556**
45	44	2020-08-20	0.278	0.092	0.036	0.203	0.078	0.042	0.064	0.197	**0.406**	**0.584**
46	45	2020-09-17	0.275	0.089	0.038	0.206	0.082	0.035	0.062	0.198	**0.402**	**0.583**
47	46	2020-10-15	0.264	0.100	0.043	0.206	0.077	0.032	0.059	0.202	**0.407**	**0.576**
48	47	2020-11-12	0.270	0.102	0.042	0.208	0.077	0.032	0.057	0.199	**0.414**	**0.573**
49	48	2020-12-10	0.278	0.103	0.037	0.217	0.077	0.030	0.054	0.189	**0.418**	**0.567**
50	49	2021-01-21	0.276	0.100	0.037	0.224	0.081	0.032	0.049	0.186	**0.413**	**0.572**
51	50	2021-02-11	0.276	0.100	0.036	0.235	0.081	0.028	0.043	0.188	**0.412**	**0.575**
52	51	2021-03-11	0.272	0.097	0.042	0.229	0.088	0.029	0.044	0.184	**0.411**	**0.574**
53	52	2021-04-15	0.278	0.094	0.043	0.213	0.089	0.031	0.048	0.189	**0.415**	**0.570**
54	53	2021-05-13	0.269	0.096	0.040	0.217	0.093	0.029	0.052	0.188	**0.405**	**0.579**
55	54	2021-06-17	0.258	0.096	0.035	0.224	0.099	0.023	0.051	0.202	**0.389**	**0.599**
56	55	2021-08-19	0.241	0.119	0.042	0.218	0.086	0.027	0.049	0.205	**0.402**	**0.585**
	56	2021-09-16	0.261	0.106	0.042	0.215	0.089	0.030	0.047	0.196	**0.409**	**0.577**

Figure B2: Top 25 contributing words and phrases in calculations of aggregate slant scores:

Nr	Left 1st set	Left 2nd set	Left 3rd set	Right 1st set	Right 2nd set	Right 3rd set
1	*sexualitet*	*vapenexport*	*arbetsvillkor*	*sport*	*terrorgrupp*	*skatt*
2	*högerparti*	*dödsstraff*	*nedskärning*	*presskonfere*	*migrant*	*försvar*
3	*luftförorening*	*våld kvinna*	*aborträtt*	*eld*	*islamisk stat*	*migrant*
4	*preventivmedel*	*högerparti*	*vapenexport*	*pressträff*	*terrorist*	*terrorgrupp*
5	*sändebud*	*luftförorening*	*marknadshyra*	*dator*	*Putin*	*terrorist*
6	*klimatkris*	*nedskärning*	*skattesänkning*	*ansikte*	*invandring*	*invandring*
7	*ojämlikhet*	*klimatkris*	*högerparti*	*terrorgrupp*	*bröst*	*bidrag*
8	*skatteparadis*	*arbetsvillkor*	*ojämlikhet*	*kilo*	*terrororganisation*	*islamisk stat*
9	*grov vapenbrott*	*ojämlikhet*	*välfärd*	*terrordåde*	*Alliansen*	*utvisning*
10	*sammankomst*	*skatteparadis*	*borgerlig regering*	*kille*	*dödsskjutning*	*medborgarskap*
11	*sjönk*	*grov vapenbrott*	*skatteparadis*	*öster*	*medborgarskap*	*liberal*
12	*jämlikhet*	*jämlikhet*	*Parisavtal*	*hjärna*	*företagare*	*migration*
13	*förena Arabemirat*	*borgerlig regering*	*jämlikhet*	*islamisk stat*	*integration*	*terrororganisation*
14	*borgerlig regering*	*representation*	*klyfta*	*ljud*	*islamist*	*integration*
15	*nödläge*	*vapenbrott*	*högerkant*	*moské*	*utanförskap*	*Alliansen*
16	*Arabemirat*	*hyresgäst*	*hyresgäst*	*präst*	*migrationspolitik*	*tillväxt*
17	*högerkant*	*klyfta*	*borgerlig parti*	*nio*	*lag ordning*	*dödsskjutning*
18	*transperson*	*högerkant*	*transperson*	*bröst*	*folkmord*	*bröst*
19	*borgerlig parti*	*Parisavtal*	*mänsklig rättighet*	*valsedel*	*skattehöjning*	*migrationspolitik*
20	*arbetare*	*transperson*	*klimatförändring*	*terrororganisation*	*jägare*	*gäng*

21	*spekulation*	*borgerlig parti*	*arbetare*	*dödsskjutning*	*extremist*	*frihet*
22	*Filippin*	*arbetare*	*rasism*	*företagare*	*Alliansparti*	*företagare*
23	*planet*	*klimatförändring*	*kärnvap*	*dans*	*vänsterkant*	*invandrare*
24	*rasism*	*rasism*	*rättighet*	*liter*	*högkonjunktur*	*lag ordning*
25	*Trump*	*Trump*	*Trump*	*vänta*	*höja skatt*	*rättsväsende*