

HOT AND COLD:

Quantifying the Variation of Sentiment in Supreme Court Confirmation Hearings

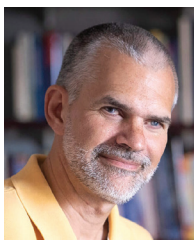
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time in software development upon graduation. Additionally, Alderton has a passion for education, and he has worked as a lecturer and curriculum creator for CS 193. He has been a teaching assistant for multiple different courses, including CS 240 and POL 300. Later in life he hopes to achieve a master's degree in computer science.

Mentors



Eric N. Waltenburg received his PhD in political science from The Ohio State University in 1994 in American politics. He joined the Purdue faculty in 1994. His research focuses on explaining the political role of high courts in democratic systems.

Dr. Waltenburg investigates these issues primarily in the context of the U.S. Supreme Court, but he has recently begun to investigate the same questions in

the context of other judicial systems, such as that of Norway. He has published articles in journals such as *American Politics Research*, *Political Behavior*, *Scandinavian Political Studies*, and *Social Science Quarterly*, and he is the author or co-author of six books on judicial politics. His most recent book (co-authored with Gunnar Grendstad, William Shaffer, and Jørn Øyrehaugen Sunde), *Proactive and Powerful: Law Clerks and the Institutionalization of the Norwegian Supreme Court*, is the first comprehensive study of law clerks in a European supreme court.



Mintao Nie received his PhD in political science at Purdue University in 2020. His research interests lie at the intersection of human rights, judicial politics, and global governance. He specifically studies how contestation and collaboration

between divergent actors determine human rights policies in both domestic and international settings. His research is published in *Du Bois Review: Social Science Research on Race and Justice* and *System Journal*. In his most recent research, Dr. Nie has explored the politics of human rights in intergovernmental organizations. In particular, he studied human rights organizations' advocacy campaigns surrounding the Universal Periodic Review at the United Nations.

Abstract

Since the appointment of John M. Harlan II in 1955, every Supreme Court nominee has testified in a Senate Judiciary Committee hearing. These hearings provide a fertile ground for senator ideologies, partisanship, and political forces to be on full display. However, little research has systematically analyzed confirmation hearings for Supreme Court nominees. In this paper, quantitative sentiment analysis is used on the transcripts of Supreme Court confirmation hearings between 1969 and 2018. By leveraging sentiment analysis, the attitudes of each of the senators during the hearings can be measured. Investigating the correlative impact that variables at the senator, institution, and nomination levels have on sentiment creates a better understanding of the factors that may influence a senator's attitude during the hearings. A positive correlative effect on sentiment was found with an increase in the percentage of the vote the nominating president received during his most recent election in the senator's home state. A positive correlation was also found when the nominating president and a senator were members of the same political party. Additionally, a statistically significant negative correlation was measured when the departing justice was a swing voter and when the hearing was aired on television. This research points to new avenues for using textual data to study partisanship and ideological polarization.

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Keywords

Supreme Court, Senate Judiciary Committee, confirmation hearings, sentiment analysis

INTRODUCTION

In 2018, Brett Kavanaugh was appointed by President Donald Trump to replace retiring Justice Anthony Kennedy on the Supreme Court. Kavanaugh's appointment proved to be highly controversial, especially once multiple women made sexual assault allegations against him (Hauser, 2018). Questioning during the Senate Judiciary Committee hearing for Kavanaugh was notably contentious. For instance, on the first day of the hearings, Senator Dick Durbin of Illinois was quoted saying, "You are the nominee of President Donald John Trump. This is a President who has shown us consistently that he is contemptuous of the rule of law. . . . It's that President who has decided you are his man" (Collinson, 2018).

The Senate Judiciary Committee hearings for Supreme Court nominees provide a keen opportunity to observe the numerous political forces in play during the appointment of a new justice to the Supreme Court. However, there has not yet been substantial research that attempts to explain the variation in senators' demeanor during the nomination hearings. A greater understanding of the attitudes during the hearings can be obtained by leveraging sentiment analysis to quantify the general attitude of the senators' statements. The goal of this project was to create a model that could explain the variance in senator sentiment using various attributes related to the individual senator, the hearing, and the Senate body as a whole.

LITERATURE REVIEW

In 2012, Lori Young and Stuart Soroka published a paper detailing their newly developed Lexicoder Sentiment Dictionary (LSD). The purpose behind creating the LSD was to have a sentiment dictionary that caters better to analyzing political communications. The LSD measures sentiment using a dictionary-based word count algorithm that counts the number of words that match a specified category in the dictionary. The LSD was created by combining three expansive lexical resources: General Inquirer (GI), Regressive Imagery Dictionary (RID), and Roget's Thesaurus.

In order to measure the effectiveness of the LSD, the authors compared it directly with six other frequently used sentiment lexicons on their ability to measure positive and negative tone in *New York Times* articles across four topics: crime, economy, environment, and international affairs. The benchmark to determine the accuracy of a sentiment dictionary is human coding. Young and Soroka organized a study

where three human coders would assign each article either a positive, negative, or neutral tone. Based upon the results from these coders, the researchers assigned a classification for each of the articles on a 5-point sentiment scale. They found that the LSD more closely aligned with the human coding of the articles compared to the other dictionaries. This indicates that the LSD is the preferred sentiment dictionary for this purpose.

Young and Soroka's paper was useful in deciding which sentiment dictionary is most appropriate for this project. Several sentiment dictionaries are available, including Affective Norms for English Words (ANEW), WordNet-Affect (WNA), and Whissell's Dictionary of Affect in Language (DAL). It can be difficult to determine which lexicon would be most appropriate for a respective research topic. However, Young and Soroka answered the question for this project by finding that the LSD is the most appropriate for political communications. Because the Senate Judiciary Committee hearings for Supreme Court nominees are highly political, it appears that the LSD would be the most appropriate dictionary for this project.

Sentimentr is an R package that measures sentiment in text (Rinker & Spinu, 2016). It was designed to address the needs of its authors, Tyler Rinker and Vitalie Spinu. Before the creation of Sentimentr, Rinker and Spinu found that other R sentiment libraries were either too slow or too inaccurate for their purposes and that packages that were quick enough did not do a sufficient job of considering valence shifters.

Valence shifters are words that impact polarized words. Polarized words are simply words that have a positive or negative meaning, which is detected by the sentiment package. There exist several different types of valence shifters. *Negators* flip the meaning of a polarized word. "Not" would be an example of a negator. The word "good" would typically be seen as positive; however, "not good" is negative. It should be noted that the Lexicoder Sentiment Dictionary considers negators, but that is the only valence shifter it considers. *Amplifiers* increase the intensity of a polarized word. Saying "really good" would be measured as more positive than just "good." *De-amplifiers* decrease the intensity of a polarized word. For instance, "barely good" is less positive than "good." The final valence shifter that Sentimentr considers is *adversative conjunctions*. This shifter looks for conjunctions that negate the previous clause. For example, in the sentence, "It was good, but I wouldn't recommend it," although the first phrase is positive, the second phrase is not, so Sentimentr would overrule the first part with the second.

Rinker and Spinu investigated the occurrence of valence shifters in several textual datasets. During the 2012 presidential debate, they found that negators occurred in 23% of sentences with polarized words and that amplifiers occurred in 18% of polarized sentences. They also investigated the occurrence of valence shifters in the speeches of President Donald Trump, finding that of polarized sentences, 14% had amplifiers and 10% had adversative conjunctions.

George Watson and John A. Stookey's 1995 book, *Shaping America: The Politics of Supreme Court Appointments*, provides detailed insight into nearly every aspect of the Supreme Court appointment process. The book's most relevant component for this project is the discussion of nomination setting. The nomination setting is defined as the variety of circumstances that surround that appointment of a new member of the Supreme Court that may affect the amount of controversy the appointment creates. Watson and Stookey recognize four primary factors that influence the nomination settings: political composition of the Senate, the level of support in the Senate for the president's programs, public opinion regarding the president, and attributes of the vacancy itself.

With the political composition of the Senate, there is expected to be less controversy for the president's nomination if the president's party holds a majority in the Senate. Additionally, it is not just a matter of which party holds a Senate majority, the size of that majority matters as well. If the party opposing the president holds a large majority over the president's party in the Senate, there is greater potential for an effective opposition campaign against the nominee to be organized.

Watson and Stookey measure Senate support for the president based upon the percentage of bills in which the Senate voted in accordance with the position of the president. A higher percentage of bills where the Senate and president aligned in preferences indicates greater Senate support for the president. Greater support for the president in the Senate is typically associated with a more seamless appointment process.

Public opinion polls from services like Gallup provide insight into the popularity of the president among the general public. If the president is unpopular with the public, it is more likely that the president's nominees will face greater opposition.

Vacancy attributes are difficult to define, as they encompass various factors that may impact the

nomination. Watson and Stookey provide several factors that would be considered vacancy attributes: “chief justice vacancy, vacancy not successfully filled with an earlier nominee, swing-vote status of the vacating justice, and special representative status of vacating justice” (Watson & Stookey, 1995, p. 50).

These measures of nomination setting will be useful when explaining the variation in sentiment between Supreme Court nomination hearings. It is hypothesized that worse nomination settings will be correlated with more negative sentiment in the hearings.

DATA COLLECTION PROCESS

The majority of the transcript data for this project were sourced from R Street (Weissmann & Marcum, 2019). When this project was in its early stages, the latest update to the dataset was from April 22, 2019. It provided the transcripts for the hearings of Lewis Powell to Neil Gorsuch, although the 1987 hearing for Robert Bork and the second set of hearings from Clarence Thomas were notable omissions from the dataset.

A few additional hearings were important to include for analysis: Clement Haynsworth, George Harrold Carswell, Harry Blackmun, Robert Bork, and Brett Kavanaugh. It is essential that failed appointments are also studied, as sentiment in these hearings might differ from sentiment in successful ones. The PDF documents for many of these hearings can easily be found on the Library of Congress’s website. However, the transcript for the Kavanaugh hearing was not yet available, so it had to be sourced via Lexis Advance as a series of text files.

The PDF data from the Haynsworth, Carswell, Blackmun, and Bork hearings needed to be converted into a format that could be processed for sentiment analysis. Unfortunately, these PDFs were scans from physical copies of the transcripts, which are difficult to use for textual analysis. Adobe Acrobat Pro DC was leveraged to convert these PDFs into plain text files. While Acrobat generally did a good job of converting these documents, the results are imperfect. For instance, due to a lack of clarity in the scans, the optical character reader (OCR) will sometimes read “Senator HRUSKA” and sometimes “Senator HRTJSKA” (i.e., “U” is sometimes mistaken for “TJ”). Mistakes like this one were corrected in an R script. It was also necessary to remove documents that were added to the record in the middle of the transcripts.

Once the Haynsworth, Carswell, Bork, and Kavanaugh transcripts were in a plain text format, various nondialogue additions to the transcript were removed. This includes “(CROSSTALK),” “(LAUGHTER),” “(inaudible),” “(OFF-MIKE),” and “(APPLAUSE).” Additionally, there were occasions where the speaker is marked as “(UNKNOWN)”; these were also removed. Statements from protestors were removed, although this was only an issue for the Kavanaugh hearings.

Once the data were cleaned of irregularities, they passed through a Python script that separates the statements by speaker. The Python script converted the text document into an Excel sheet, where column A is the speaker and column B is the statement. For the purposes of this project, opening statements and senators directly questioning the nominee were evaluated.

On October 7, 2019, R Street released an updated dataset that included both the Robert Bork hearing and the second questioning of Clarence Thomas. This provided the opportunity to compare the other data collection methodology with R Street’s for the Bork hearing. It appears that the methodologies were fairly consistent when comparing the LSD sentiment scores for the entire hearing text. My Bork data scored 0.01378956, while R Street’s was 0.01381106. For the purposes of increased consistency, R Street’s Bork data were utilized; however, it appears that the data for Carswell, Haynsworth, and Kavanaugh should be sufficiently comparable to the other hearings.

Much of the data processing takes place using R. The Excel sheets are exported as CSV files to ensure better compatibility with R. Since OCRs are not perfect at reading characters, many speaker names needed to be corrected to ensure accuracy in the data. Additionally, sometimes the OCR reads “replacement characters,” which are not valid for sentiment analysis. All non-ASCII characters are replaced with a space.

The other major aspect of data processing was assigning each of the senators their respective “bioguide_id.” Every member of Congress has a unique identifier assigned to them, and each senator’s ID had to be assigned to their statements during the hearings. The primary purpose of this is to be able to easily associate each of the senators with their corresponding NOMINATE scores, a measure of political ideology (Lewis et al., 2020).

The ultimate objective for this R script was to combine the data from each of the files into a single,

consistent CSV file. It was especially important to ensure consistency between the R Street data and the data that were processed separately. Once all the hearings were combined and the NOMINATE scores added, the CSV file could be exported for analysis.

In addition to the transcript data, each of the independent variables analyzed during this project had to also be collected and added to the dataset. In total, data on 15 independent variables were collected:

1. Most recent election vote percentage
 2. Years until next election
 3. Former House of Representatives member
 4. NOMINATE ideology score
 5. Chief justice nomination
 6. Past unsuccessful nomination
 7. Departing swing justice
 8. Departing justice has special representative status
 9. Presidential approval status
 10. Senate party split
 11. Senate support for the president
 12. Percentage of vote the president received in the senator's state during most recent election
 13. Hearing on television
 14. Senator is a member of the same party as the president
 15. Senator tenure
1. Removes contractions (e.g., "isn't" → "is not")
 2. Removes words that should not be recognized by the dictionary via punctuation. For example, "well" should not be counted as positive when it occurs at the beginning of a sentence
 3. Creates spaces around punctuation marks
 4. Converts negations to read "not" (e.g., "not very" → "not")
 5. Removes variations of words that should not be recognized by the dictionary (e.g., "may very well" → "may very xwell")
 6. Removes punctuation from capital letter acronyms (e.g., "U.S.A." → "USA")
 7. Removes punctuation from abbreviations (e.g., "Dr." → "Dr")
 8. Removes proper nouns (e.g., "Ginsburg" → "G_insburg")

These functions should improve the accuracy of the sentiment analysis. After Luxon's processing scripts have completed, the text is converted to lowercase and all symbols, numbers, and punctuation, including hyphens, are removed. At this point, the text is ready for analysis.

PREPARING FOR SENTIMENT ANALYSIS

There are a few steps that need to occur before sentiment analysis can take place. To better ensure the accuracy of sentiment analysis, the data must be preprocessed. Emily Luxon (2017) of the University of Michigan compiled an R script that provides a plethora of functions that are used to preprocess textual data before conducting sentiment analysis using the LSD. The LSD was selected for this project, primarily because it was designed with political communication in mind. Additionally, in their in-depth comparison, Young and Soroka (2012) showed that it outperforms other popular sentiment dictionaries for political communications. Eight preprocessing functions from Luxon are used with the transcripts:

MEASURING SENTIMENT

The LSD comes in two varieties. The standard LSD2015 dictionary is composed only of words or phrases that have either positive or negative sentiment associated with them. LSD2015_NEG is an extension of LSD2015 that includes negated terms, so instead of having only positive and negative categories it also has neg_positive and neg_negative. The neg_positive category is a word pattern consisting of a positive word that is preceded by a negation, while neg_negative is a negative word preceded by a negation. Utilizing this extension to the LSD should improve the accuracy of the sentiment measured. For instance, the phrase "not good" would receive a sentiment score of 0.5 by using the basic LSD2015 dictionary, which would indicate positive sentiment. However, extending the dictionary with LSD2015_NEG results in "not good" having a more appropriate score of -0.5, indicating negative sentiment. Young and Soroka (2012) found that using LSD2015_NEG resulted in a "non-negligible increase in performance" when compared to just using the standard LSD2015, so it is being utilized for this project.

The LSD is a relatively simple dictionary as polarized words do not hold any weighting. A researcher only needs to account for the number of matches for each of the respective categories. The following formula is utilized for the sentiment calculation.

$$\frac{(\text{Positive} + \text{NegNegative}) - (\text{Negative} + \text{NegPositive})}{\text{TotalWords}}$$

The formula results in a single score between -1 and 1, with negative scores associated with negative sentiment and positive scores with positive sentiment. Scores that are closer to the lower or upper bounds are more negative or positive, respectively. Texts that score close to 0 are considered neutral.

Additionally, it is important to note that whenever sentiment is measured for an individual senator, a party, or across an entire hearing, the text from all the respective statements are combined into a single block of text and then analyzed as a whole. This is based upon the recommendation from Young and Soroka (2012) in their *Lexicoder Sentiment Dictionary Codebook*. They are quoted saying:

Note that the LSD is best suited for analyzing large bodies of text. All tests were conducted on large samples at the article-level and reliability improves with the number of words analyzed. We do not recommend analyzing text at the sentence level, as it is much less likely to be reliable. (p. 3)

In addition to the LSD, the Sentimentr package for R was utilized. As described earlier, LSD only considers the negator valence shifter. While this might be completely sufficient in accurately measuring sentiment, especially since LSD has been used in many other political science research

papers, I wanted to make sure that there was not a substantial difference between using LSD and another sentiment dictionary. I selected Sentimentr due to its compatibility with R, as well as its more advanced technique in measuring sentiment. It will essentially act as a secondary measure to ensure the accuracy of my results. The same text cleansing techniques were utilized with Sentimentr.

RESULTS

Notable success was achieved with this project. I found that there were statistically significant linear correlations between several independent variables and the sentiment of a senator. I created two models: one using the Lexicoder Sentiment Dictionary and another with Sentimentr. The process of eliminating attributes was done manually. I started off with a model that contained all the attributes, then removed attributes from the model based on those with the highest p-value. For these two models, I only included independent variables that had less than 0.05 for their p-value.

However, a relatively small proportion of the overall variance in senator sentiment can be predicted using these independent variables, despite each of them being statistically significant. The adjusted R-squared value is 0.088 for Lexicoder and 0.1041 for Sentimentr (as shown in Tables 1 and 2, respectively). This means only about 9% or 10% of the variation in senator sentiment can be explained with these independent variables. Low R-squared values are to be expected with studies of this nature. Human behaviors are not easily predicted.

SAME PARTY AS THE PRESIDENT

When the senator is of the same party as the nominating president, then their sentiment during the hearings tends to be more positive. I theorize that this is due to the senator wanting to support their

	Estimate	Std. Error	t-Value	Pr(> t)
(Intercept)	0.258218	0.027356	9.439	<2e-16 ***
President State % Vote	0.002463	0.000541	4.552	7.26e-06 ***
Hearing on TV	-0.047376	0.015242	-3.108	0.002030 **
Departing Swing	-0.050203	0.014820	-3.387	0.000783 ***
Residual standard error: 0.1096 on 364 degrees of freedom				
Multiple R-squared: 0.09587; Adjusted R-squared: 0.08842				
F-statistic: 12.87 on 3 and 364 DF; p-value: 5.239e-08				
Significance codes: 0 '***', 0.001 '**'				

Table 1. R model summary using exicoder Sentiment Dictionary.

	Estimate	Std. Error	t-Value	Pr(> t)
(Intercept)	0.1967064	0.0273113	7.202	3.44e-12 ***
President State % Vote	0.0021433	0.0021433	3.778	0.000185 ***
Hearing on TV	-0.037245	0.015044	-2.476	0.013754 *
Same Party	0.0298179	0.0121204	2.460	0.014353 *
Departing Swing	-0.050203	0.0146321	-3.630	0.000324 ***
Residual standard error: 0.1079 on 363 degrees of freedom				
Multiple R-squared: 0.1139; Adjusted R-squared: 0.1041				
F-statistic: 11.66 on 4 and 363 DF; p-value: 6.39e-09				
Significance codes: 0 '***', 0.01 '**', 0.05 '*'				

Table 2. R model summary using Sentimentr.

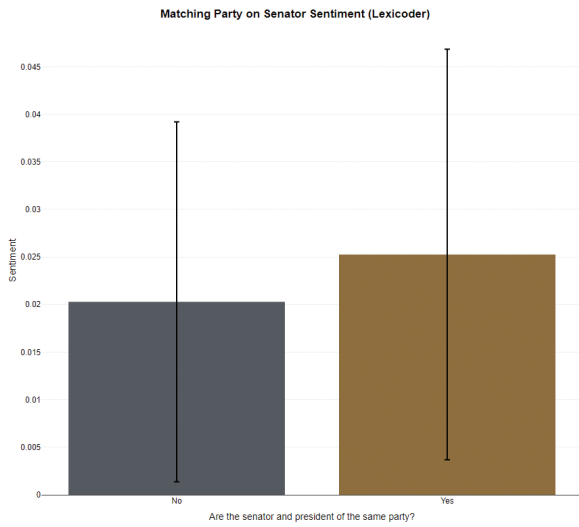


Figure 1. President and senator belong to same party (Lexicoder).*

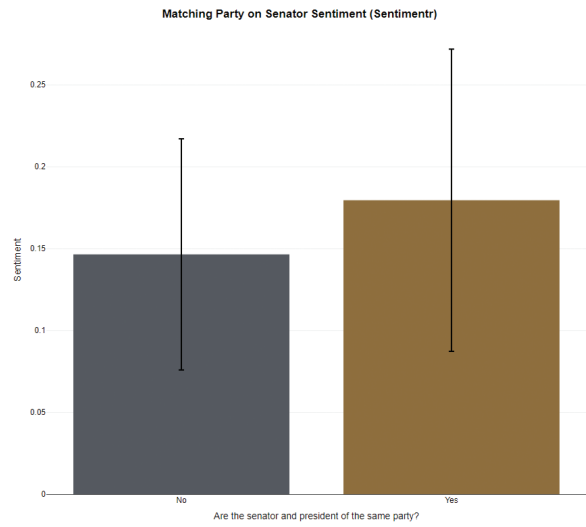


Figure 2. President and senator belong to same party (Sentimentr).*

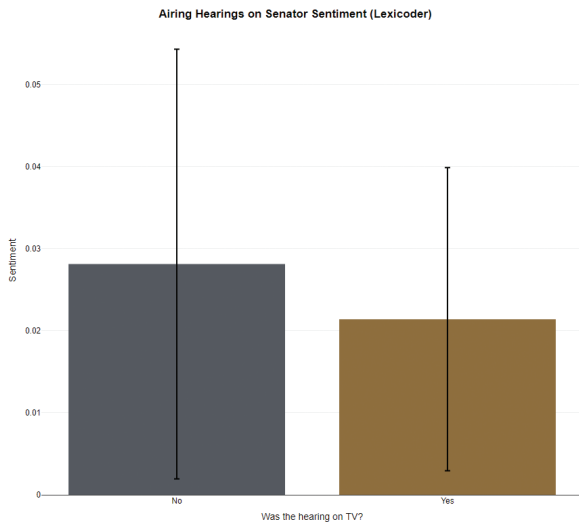


Figure 3. Hearing was aired on television (Lexicoder).*

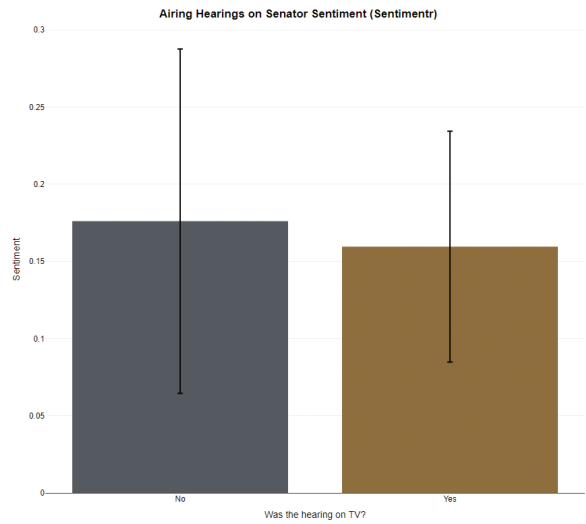


Figure 4. Hearing was aired on television (Sentimentr).*

*Black bars on the bar charts represent 1 standard deviation away from the average.

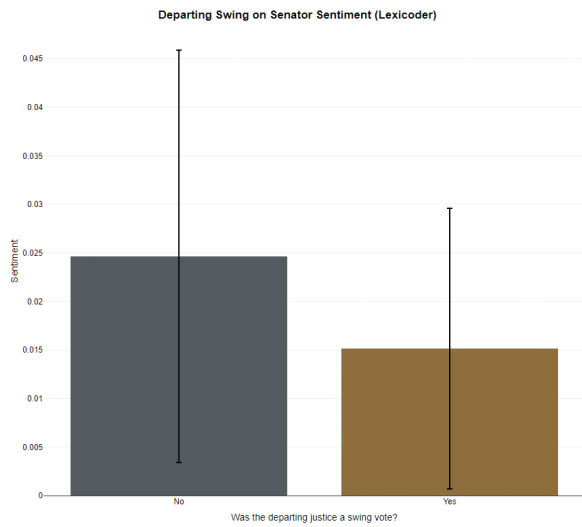


Figure 5. Departing justice was a swing voter (Lexicoder).*

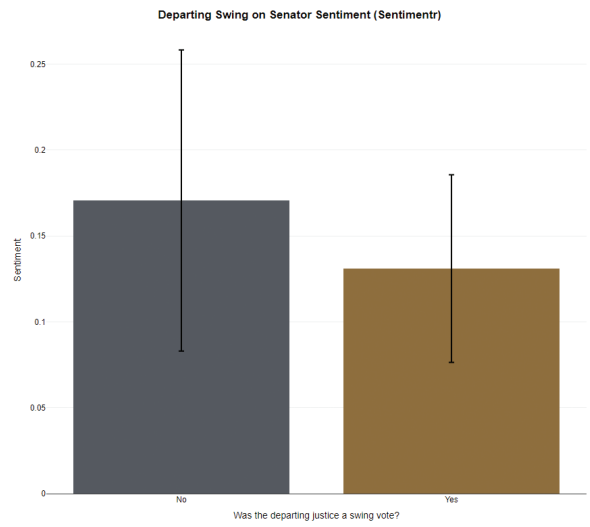


Figure 6. Departing justice was a swing voter (Sentimentr).*

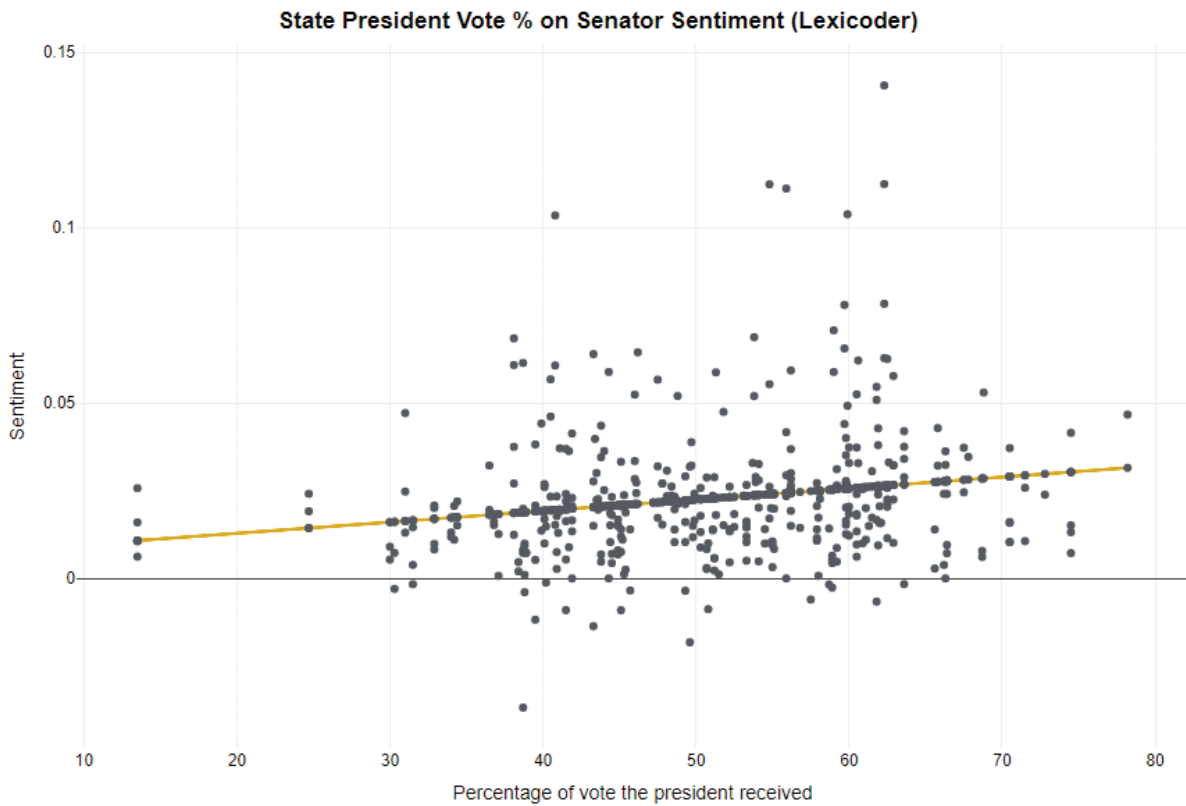


Figure 7. Percentage of vote the president received in the senator's state (Lexicoder).

*Black bars on the bar charts represent 1 standard deviation away from the average.

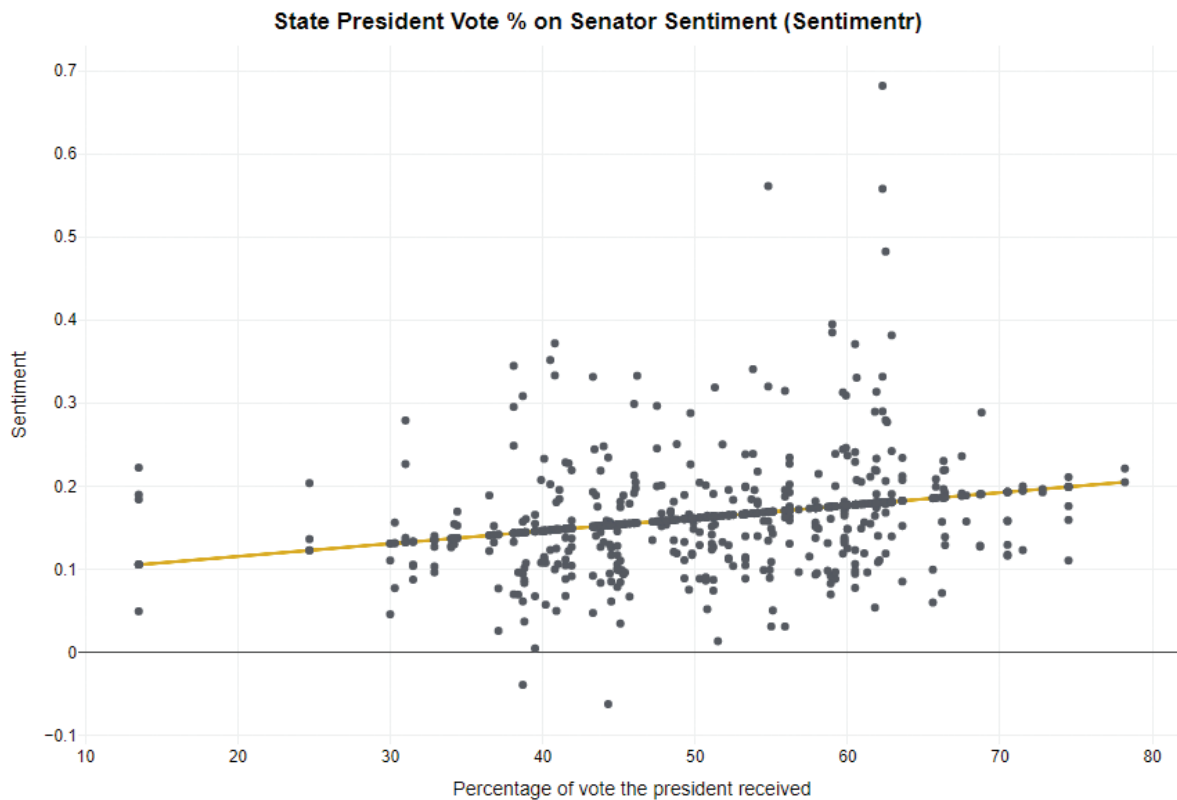


Figure 8. Percentage of the vote the president received in the senator’s state (Sentimentr).

party’s president in an effort to show party unity. It is important to note that significance was only found for this independent variable with the Sentimentr methodology. The plots shown in Figures 1 and 2 represent mean sentiment, with the black error bars representing one standard deviation.

HEARING AIRED ON TELEVISION

Since the hearing for Justice Sandra Day O’Connor in 1981, every Supreme Court nominee’s confirmation has been aired on television. I found that senators tend to be more negative in hearings that are aired on television (see Figures 3 and 4). This is likely due a cultural shift in the hearings. Bringing television cameras into the hearing room made the hearings themselves much more public, and senators could be scrutinized for their actions during the hearings. Before the hearings were televised, it was commonplace for only a few senators to ask questions (Farganis & Wedeking, 2014, p. 23). Today, however, it would be considered odd if a senator did not ask a question during a confirmation hearing. As a result of this cultural shift in 1981, senators might be more critical during the hearings in an effort to show that they are properly vetting the nominees.

DEPARTING SWING JUSTICE

If the departing justice from the Court was known to be a swing vote, then senators tend to be more negative (see Figures 5 and 6). This might be attributed to the senators being more critical of the appointed justice in an effort to get the president to appoint a more moderate replacement.

SENATOR’S STATE PRESIDENTIAL VOTE PERCENTAGE

In my opinion, the percentage of the vote the president received in the senator’s state is the most interesting contributing attribute in the model. This variable essentially means that senators tend to be more positive during the confirmation hearings if the nominating president performed well in their home state during the most recent election (see Figures 7 and 8). I believe this correlation could potentially be explained by the senators trying to either better represent their state’s political preferences or simply improve their reelection chances.

DISCUSSION

The results from this project imply that senators may be strategic in their sentiment during the Senate Judiciary Committee hearings for Supreme Court nominees. The correlation between sentiment and the percentage of the vote that a president received during the most recent election in the senator's home state is particularly fascinating. This project may indicate that senators consider various factors in determining how they will question the nominee. I plan to continue to investigate this, as I am just scratching the surface of what can be learned from using sentiment analysis with this topic.

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