

Heard or Halted? Analyzing the Emotional Tone of Judicial Interruptions

PPOL6801 Text As Data - Final Project

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1. Abstract

This project investigates the role of gender in Supreme Court oral arguments by analyzing how interruptions affect the semantic content and emotional tone of advocates' speech. Using the ConvoKit Supreme Court Corpus (2010–2019), we extract 12,663 speech chunks from advocate-justice interactions. We address two central questions: (1) Do interruptions shift the semantic meaning of an advocate's argument? (2) Do interruptions directed at female advocates contain more negative sentiment than at male advocates? We employed GloVe-based embeddings to measure semantic shifts and apply lexicon-based sentiment analysis for emotional valence. We found that while semantic similarity remains high between speech before and after interruptions, and interruptions toward female advocates tend to have higher negativity. These findings contribute to ongoing discourse on gendered dynamics in elite deliberative settings and demonstrate the value of computational linguistics in empirical legal studies.

2. Introduction

Oral arguments before the U.S. Supreme Court represent one of the most consequential forms of institutional deliberation in American governance, shaping legal outcomes through the most public and visible part of the decision-making process. Within this setting, interruptions by justices are not merely conversational phenomena; they may reflect—and reinforce—underlying power asymmetries among participants. Prior research has shown that female advocates are significantly more likely to be interrupted than male counterparts, even when controlling for experience and institutional position (Cai et al., 2021). While these findings highlight the gendered dynamics of courtroom discourse by quantifying interruption behavior in terms of frequency, less is known about the consequences of such interruptions—specifically, whether they alter the content or emotional tone of an advocate's message.

Therefore, our study extends the original idea to investigate the discursive effects of interruptions during Supreme Court oral arguments, with a particular focus on gender. We pose two primary research questions:

1. *Do interruptions alter or preserve the core semantic content of an advocate's argument?*
2. *Are interruptions directed at female advocates characterized by more negative sentiment than those directed at male counterparts?*

Our aim is twofold: (1) to evaluate whether interruptions disrupt not only the flow but also the substance of advocacy, and (2) to assess whether gendered patterns in rhetorical effect are present in how interruptions are enacted. By combining computational techniques with institutional context, this study contributes to a growing body of work at the intersection of political communication, judicial behavior, and gender studies.

Gender and Discourse | Supreme Court Oral Arguments | Interruptions | Sentiment Analysis | Semantic Similarity |
Lexicon-Based Analysis | Computational Linguistics

37 3. Data and Methods

38 3.1. Data Source and Unit of Observation

39 This study draws on the ConvoKit Supreme Court Corpus, a structured dataset of transcripts
40 before the United States Supreme Court. Our analysis focuses on the 2010–2019 term years,
41 yielding a final analytic sample of 12,663 speech chunks delivered by legal advocates to study
42 the most recent trends.

43 Each chunk represents a continuous segment of speech by an advocate, bounded by a complete
44 turn in interaction with a single justice. These chunks were created by grouping together advocate
45 utterances that occur between interruptions or pauses in dialogue. Each chunk captures a coherent
46 portion of an advocate’s argument — typically a few sentences long — and is treated as a single
47 unit of observation.

48 We followed the filtering logic established in the original study by Cai et al. (2022), which
49 excludes cases with incomplete metadata, unidentifiable advocate turns, or topics likely to
50 introduce strong confounds in emotional language. In particular, cases involving highly emotive
51 issues such as abortion—identified using a `female_issue` flag—were removed to better
52 isolate gendered interactional dynamics from topic-driven sentiment. Although the original
53 implementation was adapted for our environment, the underlying filtering criteria and rationale
54 remain consistent with the authors’ design.

55 3.2. Feature Construction

56 Interruptions were programmatically identified by detecting sequences in which an advocate’s
57 utterance was prematurely cut off and immediately followed by a justice’s interjection. In the
58 transcript data, such interruptions are typically marked by double dashes (“—”) to indicate
59 an abrupt cutoff or ellipses (“...”) to represent trailing speech. These textual patterns were
60 cross-referenced with speaker metadata to confirm that the next speaker was a justice, ensuring
61 that only justice-initiated interruptions were flagged.

62 The example below shows an interruption exchange between an advocate and Justice Scalia:

63 **Douglas Laycock (Advocate):**

64 “Well, some courts have said yes. There’s very little in this record about full beards and
65 whether they’re safe or whether they’re dangerous. . . ”

66 **Justice Scalia (Interrupting):**

67 “Mr. Laycock, the problem I have with— with your client’s claim. . . ”

68 In this exchange, the justice redirects the conversation mid-sentence towards his own analogy,
69 interrupting the advocate’s argument. Such interruptions were automatically identified at the
70 utterance level and used to label whether a given speech chunk was interrupted. These interruption
71 labels were critical in structuring both the sentiment and semantic analyses that followed.

72 4. Analysis

73 4.1. Semantic Shifts: Methodology and Implementation

74 To evaluate whether interruptions alter the semantic content of advocates’ arguments, we computed
75 sentence-level semantic embeddings using pre-trained GloVe word vectors (100-dimensional).
76 Each chunk was first preprocessed using standard text-cleaning procedures: conversion to
77 lowercase, removal of punctuation, and expansion of contractions. Tokens were then extracted
78 and filtered to retain only those present in the GloVe vocabulary.

79 For each token-matched chunk, we calculated a sentence-level embedding by averaging the
80 GloVe vectors corresponding to its valid tokens. This yielded a single vector representation per
81 chunk, capturing its overall semantic content in continuous vector space.

82 To compare speech under different interruption conditions, we grouped chunks by advocate

83 and interruption status. For each advocate, we aggregated two composite embeddings: one
84 representing their *interrupted chunks*, and one for their *non-interrupted chunks*.

85 We then calculated the cosine similarity between these two embeddings for each advocate.
86 High cosine similarity values (greater than 0.85) suggest semantic consistency across interruption
87 status, while lower values may indicate that interruptions correspond with shifts in argumentative
88 content.

89 4.2. Gendered Sentiment: Lexicon-Based Analysis

90 To investigate whether interruptions toward female advocates are more emotionally negative
91 than those toward male advocates, we conducted a lexicon-based sentiment analysis focused on
92 emotional tone. We restricted the analysis to interrupted chunks of speech that had been marked
93 with labels and applied the NRC Emotion Lexicon, which associates English words with specific
94 emotions (e.g., anger, fear, sadness) and sentiment polarity (positive or negative).

95 Each token in a chunk was matched to its corresponding sentiment label. For each interrupted
96 chunk, we computed:

- 97 - The total number of emotion-labeled words,
- 98 - The negative emotion ratio: the proportion of emotion-labeled words that associated with
99 negative polarity or negative emotions (anger, fear, disgust, sadness, or negative polarity)

100 We then aggregated negative sentiment ratios by advocate's gender to assess overall trends.
101 A Welch two-sample t-test was performed to compare group means, followed by an ordinary
102 least squares (OLS) regression model. The regression included control variables for advocate
103 experience, case year, and ideological alignment with the justice, in order to isolate gender as a
104 factor influencing the emotional tone of interrupted speech.

105 5. Results

106 5.1. Semantic Effects of Interruptions

107 To evaluate whether interruptions alter the semantic content of an advocate's argument, we
108 computed the cosine similarity between the average embeddings of interrupted and uninter-
109 rupted speech chunks for each advocate. These sentence-level embeddings serve as vectorized
110 representations of each chunk's semantic content.

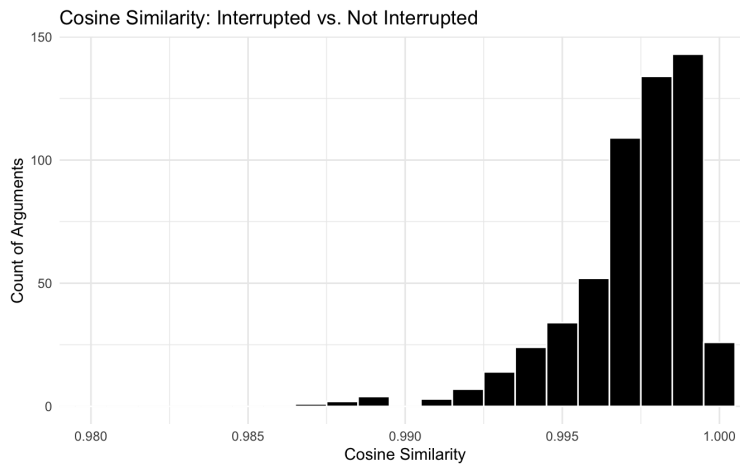


Fig. 1. Distribution of Semantic Overlap Between Pre- and Post-Interruption Speech

111 The distribution of cosine similarity scores is shown in Figure 1. The scores are tightly
 112 clustered between 0.98 and 1.00, with a pronounced concentration above 0.99. The mean cosine
 113 similarity is approximately 0.997, indicating an exceptionally high degree of semantic overlap
 114 between interrupted and uninterrupted chunks of speech from the same advocate.

115 The near-perfect cosine similarity implies that interruptions do not significantly shift the
 116 semantic meaning of advocates' arguments, at least as captured by GloVe-based representations.
 117 Rather, interruptions may disrupt the rhetorical flow or perceived coherence without altering
 118 substantive content. This finding aligns and supports the prior interpretation that interruptions
 119 may be more performative or strategic—serving interactional or hierarchical functions—rather
 120 than substantive in altering the content of legal advocacy.

Table 1. Summary Statistics of Cosine Similarity Scores

Min	Median	Mean	Max
0.8899	0.9977	0.9970	0.9999

121 5.2. Gendered Sentiment of Interruptions

122 5.2.1. Descriptive Patterns

123 To assess whether interruptions directed at female advocates are more negatively toned, we
 124 conducted a lexicon-based sentiment analysis using the NRC Emotion Lexicon. We focused on
 125 interrupted chunks only and categorized words according to both emotional valence (e.g., anger,
 126 fear) and polarity (positive or negative). For each chunk, we computed a negative sentiment ratio,
 127 defined as the proportion of emotion-labeled words that were classified as negative.

128 Figure 2 presents the distribution of negative emotion proportions by advocate gender. Although
 129 the overall patterns are broadly similar, interruptions directed at female advocates show slightly
 130 higher proportions of anger and disgust, whereas male-directed interruptions exhibit marginally
 131 higher levels of fear and sadness. These variations are modest, indicating that emotional
 132 tone—when broken down by individual emotion categories—does not differ dramatically by
 133 gender.

134 Figure 3 displays the distribution of negative sentiment ratios across interrupted chunks. Female
 135 advocates exhibit a higher median and upper quartile in negative sentiment ratio compared
 136 to male advocates. Although the distributions overlap considerably, this pattern suggests that
 137 interruptions directed at women tend to be associated with slightly more emotionally negative
 138 language. While subtle, this difference is supported by subsequent statistical tests and points to a
 139 small but meaningful disparity in the emotional valence of interruptions by gender.

140 5.2.2. Statistical Evidence

141 Followed, we evaluated gender differences in the emotional tone of interruptions by applying
 142 a Welch two-sample t-test and an ordinary least squares (OLS) regression using the negative
 143 sentiment ratio as the outcome variable. The Welch t-test reveals a statistically significant
 144 difference between the two groups ($p < 0.01$), with female advocates experiencing a higher
 145 average proportion of negative emotion in their interrupted speech chunks than males. Although
 146 the absolute difference in means is modest with approximately 2%, the result suggests a consistent
 147 disparity in how interruptions unfold by gender.

148 To account for potential confounding variables, we also estimated an OLS regression model
 149 controlling for advocate experience, case year, and ideological dynamics between the advocate
 150 and the justice. As shown in Appendix Table A2, the effect of gender remains statistically

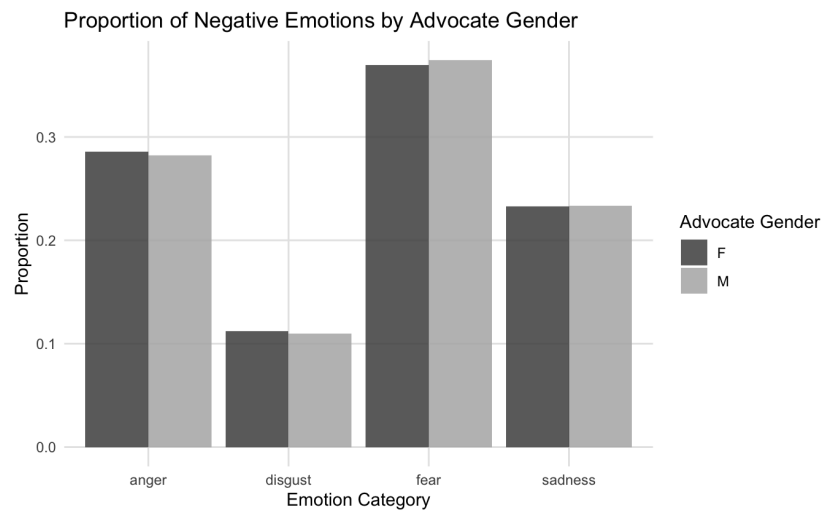


Fig. 2. Proportion of Negative Emotions in Interrupted Chunks by Advocate Gender

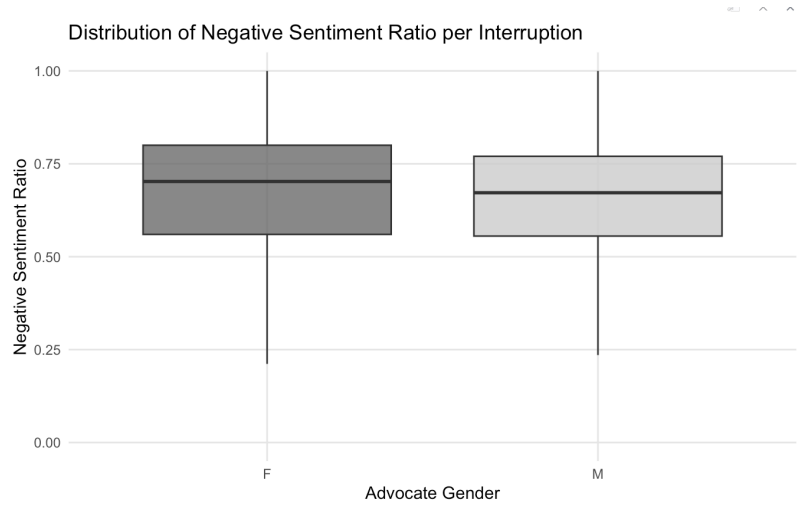


Fig. 3. Distribution of Negativity Ratios in Interrupted Chunks by Advocate Gender

151 significant: interruptions directed at female advocates are associated with a higher proportion of
 152 negative sentiment, even after adjusting for these covariates. At the same time, past experience
 153 tempers the negativity of interruptions, while ideological alignment with justices does not offer
 154 obvious protection from negative tone.

155 These findings reinforce the descriptive trends and underscore that gendered differences
 156 in the emotional tone of interruptions are not merely artifacts of topic selection or advocate
 157 characteristics. While the magnitude of the effect is small, its consistency across statistical
 158 approaches adds weight to the interpretation that female advocates face qualitatively different
 159 rhetorical dynamics during oral argument.

Table 2. Key Predictors of Negative Sentiment Ratio in Interruptions

Variable	Estimate	Std. Error	t value	p-value
Advocate Gender (Male)	-0.0114	0.0052	-2.174	0.0298
Advocate Experience (Integer)	-0.0022	0.0004	-5.402	<0.001 ***

Note: Coefficients from OLS regression using negative sentiment ratio as the dependent variable. Gender effect is relative to female advocates.

* $p < .05$, ** $p < .01$, *** $p < .001$

160 5.2.3. LDA for Topic Modeling

161 To explore whether gender differences in emotional tone might reflect underlying differences
 162 in the subject matter of advocate speech, we applied Latent Dirichlet Allocation (LDA) topic
 163 modeling. Specifically, we implemented a six-topic solution using a document-term matrix
 164 constructed from cleaned chunk text. Each chunk was assigned a probability distribution across
 165 topics, allowing us to examine whether certain themes were more prevalent among male or
 166 female advocates, and whether topic content might explain the observed sentiment patterns.

167 As a robustness check, we analyzed topic distributions by gender and incorporated topic
 168 weights into regression models predicting negative sentiment. average topic proportions were
 169 nearly identical across male and female advocates, and the gender coefficient in regression models
 170 remained significant after controlling for topic weights. These results indicate that topic content
 171 did not account for the gender-based disparities in emotional tone. In addition, top terms across
 172 the six topics showed substantial lexical overlap. Words such as court, justice, law, and statute
 173 appeared frequently in all topics, highlighting a core limitation of using LDA in this setting:

174 - Legal discourse is characterized by a highly constrained and repetitive vocabulary, driven
 175 by institutional formality and repeated references to statutes and precedent. This reduces topic
 176 heterogeneity and undermines LDA's ability to form meaningful distinctions.

177 - LDA also assumes that documents are sufficiently long to exhibit a mixture of topics.
 178 In contrast, individual speech chunks in this corpus tend to remain narrowly focused, often
 179 addressing a single legal issue or responding directly to a justice's question.

180 - For a study of emotion and interruption dynamics, topic groupings must capture differences
 181 in legal content—not just “court talk” or standardized courtroom speech.

182 In sum, while topic modeling was a conceptually valid extension, the constrained language of
 183 Supreme Court oral arguments limited its utility. We interpret the LDA results primarily as a
 184 reflection of domain-specific challenges, rather than evidence of meaningful topic-based gender
 185 divergence.

186 6. Discussion

187 6.1. Conclusions

188 This study investigated how interruptions during the U.S. Supreme Court oral arguments affect
 189 both the semantic content and emotional tone of advocate speech, with particular attention to
 190 gender dynamics. Using GloVe-based embeddings, we found that interrupted and uninterrupted
 191 statements from the same advocate had extremely high cosine similarity, suggesting that
 192 interruptions do not significantly alter the semantic substance of arguments. However, lexicon-
 193 based sentiment analysis revealed that interruptions directed at female advocates were associated
 194 with slightly higher negative sentiment ratios, a consistent finding even after controlling for
 195 potential confounders such as experience, ideology, and case year.

196 6.2. *Theoretical and Empirical Contributions*

197 This study advances understanding of gendered power dynamics in institutional discourse by
198 shifting focus from the frequency of interruptions to their rhetorical consequences. We assess
199 whether interruptions alter the semantic and emotional content of legal arguments, linking
200 conversational disruptions to broader concerns about epistemic authority and discursive equity
201 and discursive equity in elite legal settings.

202 Methodologically, we integrate structured transcript metadata with computational textual
203 analysis, applying sentence embeddings and emotion lexicons to Supreme Court oral arguments.
204 Our findings demonstrate both the potential and limitations of using pre-trained language
205 models in formal legal discourse and highlight persistent gendered patterns in how interruptions
206 unfold—even in highly constrained environments, offering a replicable approach for scholars of
207 political communication, judicial behavior, and computational social science.

208 6.3. *Limitations and Future Directions*

209 While our results are suggestive, several limitations remain. First, our sentiment analysis relies
210 on dictionary-based methods that may miss nuanced or sarcastic tones. Second, although
211 interruptions were detected programmatically, our binary categorization (interrupted vs. not) may
212 oversimplify the complex dynamics of turn-taking in oral arguments. Not all interruptions carry
213 the same weight; some may be brief clarifications, while others may sharply derail or redirect an
214 advocate’s argument. This dichotomous approach overlooks the variation in interruption severity,
215 tone, and intent.

216 As a promising direction for future work, researchers could move beyond binary labels to
217 incorporate measures of interruption intensity—such as the frequency built on prior work, or the
218 duration between interruptions. This would enable a more granular analysis of whether frequent
219 or clustered interruptions have compounding rhetorical effects.

220 Additionally, efforts to disentangle interruption intent using dialogue structure or speech-act
221 classification may help distinguish between adversarial and cooperative interruptions, yielding a
222 more comprehensive understanding of gendered interaction styles. Finally, extending this work
223 through justice-level analysis or cross-institutional comparisons (e.g., lower courts, international
224 tribunals) would broaden its empirical relevance and help contextualize findings within the
225 broader landscape of institutional discourse generalizability.

Table 1: Welch Two-Sample *t*-Test: Negative Sentiment Ratio by Advocate Gender

Statistic	Value	Notes
Mean (Female Advocates)	0.6614	
Mean (Male Advocates)	0.6467	
<i>t</i> Statistic	2.6623	Welch Two-sample <i>t</i> -test
Degrees of Freedom	1729.7	
<i>p</i> -value	0.0078	**
95% Confidence Interval	[0.0039, 0.0256]	Difference in group means

Note: Welch's *t*-test evaluates whether the difference in negative sentiment ratio between female and male advocates is statistically significant.

* $p < .05$, ** $p < .01$, *** $p < .001$

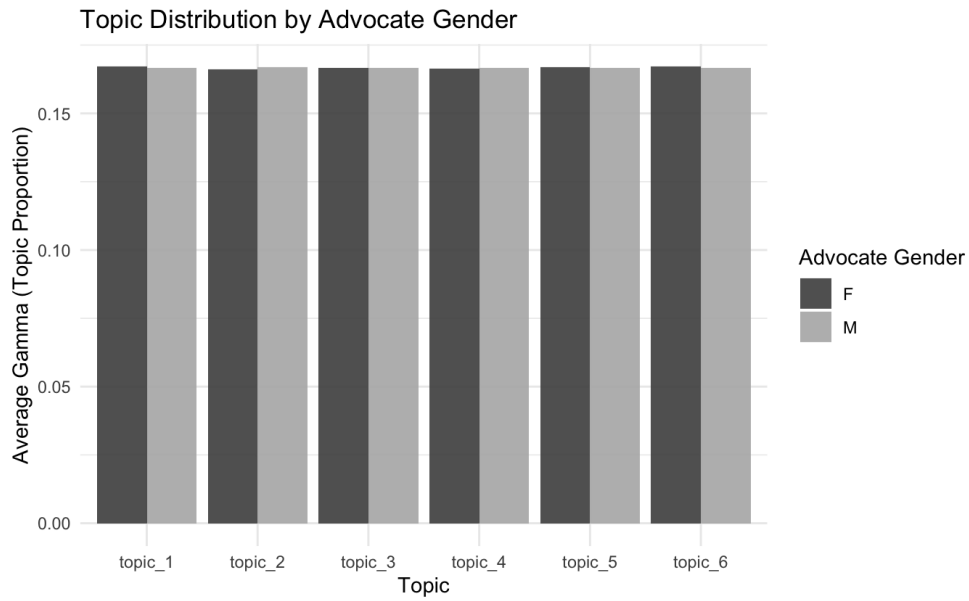
Table 1. Welch Two-Sample *t*-Test Results

Variable	Estimate	Std. Error	p-value
(Intercept)	-1.4088	1.2816	0.2717
Advocate gender (Male)	-0.0114*	0.0052	0.0298
Advocate experience (int)	-0.0022***	0.0004	< 0.001
Case year	0.0010	0.0006	0.1064
Female issue ^a	—	—	—
Advocate ideology (Liberal)	0.0061 [†]	0.0035	0.0861
Ideology matches	0.0018	0.0036	0.6196
Residual Std. Error	0.1785 (df = 10291)		
Multiple R^2	0.0041		
Adjusted R^2	0.0036		
F-statistic	8.501 on 5 and 10291 DF, $p < 0.001$		

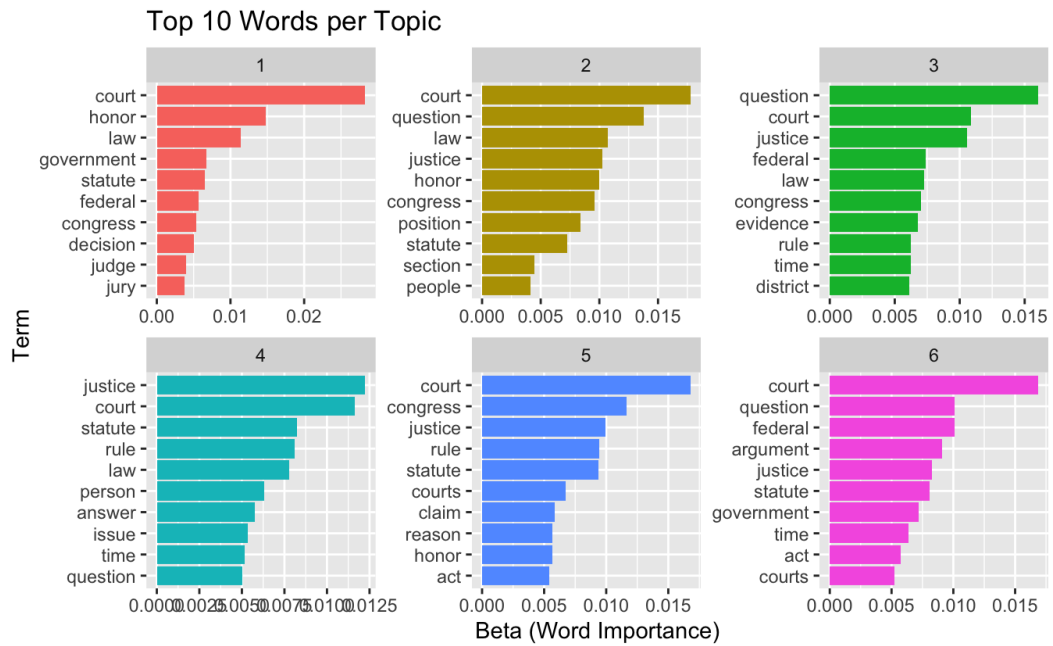
* $p < 0.05$ *** $p < 0.001$ [†] $p < 0.1$

^a Variable dropped due to collinearity or lack of variance.

Table 2. Regression Results: Predicting Negative Sentiment Ratio in Interruptions



Appendix Figure A1. Topic Distribution by Advocate Gender



Appendix Figure A2. Top 10 Words per Topic

227 **References**

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