Online Appendix to Political Threads in Legal Tapestry: A Computational Analysis of Executive Branch Legal Interpretation, 1934–2022

This Online Appendix supports the analysis in Reilly S. Steel, *Political Threads in Legal Tapestry: A Computational Analysis of Executive Branch Legal Interpretation, 1934–2022*, forthcoming in the *University of Pennsylvania Journal of Constitutional Law*. It contains two sections. Section A is a technical appendix containing details for some of the empirical methods used in the Article. Section B contains supplemental figures and tables.

A. Technical Appendix

1. *Topic Model Details*

This subsection provides details on the topic models described in Part III. To estimate these models, I use the approach proposed by Professors Margeret E. Roberts, Brandon M. Stewart & Dustin Tingley[1] and implemented in the `R` package `stm`. As noted in the Article, topic models are unsupervised machine learning algorithms that allow the researcher to uncover the "main themes" underlying a large collection of texts.[2] The researcher starts by choosing a fixed number of topics and then allows the algorithm to learn the topics that best describe the data.[3] For each topic, the model tells the researcher which words are in the topic and how likely it is that each word will be used.[4] For each document, the model provides the proportion of topics in the document. For example, the model might give three topics (A, B, C) and then tell the researcher that document five is a mixture between the three topics with proportions (0.5, 0.4, 0.1). It is then up to the researcher to use domain knowledge and judgment to label the topics based on the language used in each topic as well as the content of emblematic documents.

After testing a range of different numbers of fixed topics and comparing model performance under each, I settle on thirty-seven topics as a sensible number that balances model fit with topic coherence, and I estimate this model on the unigrams version of the document–term matrix.[5] To determine the appropriate label for each topic, I start by reviewing the top words associated with each topic, as reflected by the probability with which the word is used and by the words that distinguish topics from one another. In many cases, this is sufficient to give me a strong sense of the topic, but I nevertheless confirm my intuition by examining excerpts from at least five representative documents for each topic. Following the labeling of topics, I further subdivide these topics into nine "meta-topics" to make them more digestible. Some of these meta-topics overlap conceptually, but they help to surface trends that would otherwise be difficult to discern in the large number of topics. Table 1 reports summary statistics on the frequency of these meta-topics by period. Additional information on topic labels, topic frequencies, words associated with each topic, and meta-topic assignments is contained in Tables A2 and A3 in the Online Appendix.

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[1] Professors Margeret E. Roberts, Brandon M. Stewart & Dustin Tingley, 91 J. STAT. SOFT. 1 (2019).

[2] David M. Blei, *Probabalistic Topic Models*, 55 COMMC'NS ACM 77, 77 (2012). *See also* GRIMMER, ROBERTS, AND STEWART, *supra* note 1, at 147–61 (providing an overview of topic models).

[3] Blei, *supra* note 1, at 77.

[4] Formally, a topic is a "distribution over a fixed vocabulary," where the vocabulary is given by the unique tokens or "types" in the corpus. *Id.* at 78.

[5] Fully replicable details on model testing and selection will be contained in the `R` code made available with the Article.

2. *Mathematical Details for Partisan Difference Measurements*

This subsection presents formal mathematical details for the estimation of token-level partisan tilt and the overall partisan gap described in Section IV.A.

I seek to estimate a partisan tilt score for each token based on the natural logarithm of the odds that an observer with a neutral prior would assign to the sitting president being a Republican (R) versus a Democrat (D), given the single token observed.[6] To do so, I assume a simple model underlying the generation of opinions in which the observed token counts are draws from a multinomial distribution, with different choice probabilities for each party.[7] Formally, let $\mathbf{n}_i$ be a vector of counts for which each unique token in the corpus (i.e., type) appears in opinion i. For each opinion i, I assume $\mathbf{n}_i \sim \text{Multi}(N_i, \pi^{P_i})$, where $N_i = \sum_j n_{ij}$ is the total count of tokens in opinion i, $P_i \in \{R, D\}$ is the party of the sitting president for opinion i, and π^{P_i} is a vector of choice probabilities that depends on the party of the sitting president. Let $\mathbb{P}(P_j)$ be the prior probability that the president for token j is a member of party P, which I assume equals $\frac{1}{2}$ for each party, and let $\mathbb{P}(P_j|x_j)$ be the probability that the sitting president is a member of party P given a single instance of token j. For each token j, I seek to estimate $\rho_j := \log\left[\frac{\mathbb{P}(R_j|x_j)}{\mathbb{P}(D_j|x_j)}\right]$.

Given $\mathbf{n}_i \sim \text{Multi}(N_i, \pi^{P_i})$, the draw of a single token takes a categorical distribution with choice probabilities π^{P_i}. It follows from Bayes' rule and $\mathbb{P}(R_j) = \mathbb{P}(D_j) = \frac{1}{2}$ that

$$\mathbb{P}(P_j|x_j) = \frac{1}{2}\frac{\pi_j^R}{\pi_j}. \tag{1}$$

[6]These token-level scores are similar to the document-level scores estimated in Nick Beauchamp, Using Text to Scale Legislatures with Uninformative Voting 7–8, 27–28 (Aug. 8, 2012) (unpublished manuscript), http://nickbeauchamp.com/work/Beauchamp_scaling_current.pdf, and RICHARD A. NIELSEN, DEADLY CLERICS: BLOCKED AMBITION AND THE PATHS TO JIHAD 114–24, 209–11 (2017).

[7]For other work that assumes a multinomial distribution underlying the speech-generating process, see Matthew Gentzkow, Jesse M. Shapiro & Matt Taddy, *Measuring Group Differences in High-Dimensional Choices: Method and Application to Congressional Speech*, 87 ECONOMETRICA 1307, 1312–13 (2019), and Burt L. Monroe, Michael P. Colaresi & Kevin M. Quinn, *Fightin' Words: Lexical Feature Selection and Evaluation for Identifying the Content of Political Conflict*, 16 POL. ANALYSIS 372, 383–84 (2008).

Therefore,

$$\frac{\mathbb{P}(R_j|x_j)}{\mathbb{P}(D_j|x_j)} = \frac{\pi_j^R}{\pi_j^D} \tag{2}$$

$$\log\left[\frac{\mathbb{P}(R_j|x_j)}{\mathbb{P}(D_j|x_j)}\right] = \log\left(\frac{\pi_j^R}{\pi_j^D}\right) \tag{3}$$

$$\rho_j = \log\left(\frac{\pi_j^R}{\pi_j^D}\right). \tag{4}$$

To estimate ρ_j, we need to obtain estimates for π_j^R and π_j^D. Let n_j^P be the number of occurrences of token j in party P's opinions. Then the maximum likelihood estimator for π_j^P is $\frac{n_j^P}{\sum_{j'} n_{j'}^P}$. With Laplace smoothing, the estimator becomes $\frac{n_j^P+1}{\sum_{j'}(n_{j'}^P+1)}$.[8] To mitigate finite-sample bias,[9] I use a "leave-one-out" version of this estimator. First, for each opinion, I initially estimate the token-level choice probabilities using data from all the *other* opinions, leaving out the opinion before me, and calculate an opinion-specific estimate of ρ_j. Second, I take the weighted average of these opinion-specific token-level estimates for my final estimate of ρ_j.

Formally, the estimator for the party-specific probability of observing j in opinion i, $\pi_{j(i)}^P$, is given by

$$\hat{\pi}_{j(i)}^P = \frac{n_j^{P-i}+1}{\sum_{j'}(n_{j'}^{P-i}+1)}, \tag{5}$$

where n_j^{P-i} denotes the number of occurrences of token j in party P's opinions excluding opinion i.

The opinion-specific estimator for ρ_j is given by

$$\hat{\rho}_{j(i)} = \log\left(\frac{\hat{\pi}_{j(i)}^R}{\hat{\pi}_{j(i)}^D}\right), \tag{6}$$

where $\hat{\pi}_{j(i)}^P$ is defined by equation (5).

The final estimator for ρ_j is then given by the weighted average of the opinion-specific token-level estimates across all instances of the token:

$$\hat{\rho}_j = \frac{1}{n_j}\sum_i n_{ij}\hat{\rho}_{j(i)}, \tag{7}$$

[8] *See* NIELSEN, *supra* note 6, at 210 n.4. Laplace smoothing is appropriate because some tokens may appear in only one party's opinions. *See id.*

[9] For an explanation of this bias, see Gentzkow, Shapiro & Taddy, *supra* note 7, at 1314–15.

where $n_j = \sum_i n_{ij}$ denotes the number of instances of token j in the corpus, $\hat{\rho}_{j(i)}$ is defined by equation (4), and the second sum adds up partisan tilt scores for all instances of token j in opinion i.

Using these estimates, I measure the overall partisan gap during period t as

$$PartisanGap_t = |\overline{\rho}_t^R - \overline{\rho}_t^D|, \tag{8}$$

where $\overline{\rho}_t^P$ is defined as the mean token-level partisan tilt estimate ($\hat{\rho}_j$) across all token instances under party P during period t.

3. *Word Embeddings Estimation*

This subsection describes the methods used to estimate word embeddings for the analyses in Part IV of the Article.

I start by preprocessing the corpus. Preprocessing is somewhat different here than with the bag words model: here, I expand the list of stop words to filter out words that lack substantive meaning, and I decline to set minimum term frequency thresholds before estimating the embeddings. I do set minimum term frequency and document frequency thresholds when determining candidate nearest neighbors for the executive power analysis. Specifically, candidate nearest neighbors are limited to words that appear at least eight times in the corpus and in at least four documents. I use these thresholds to mitigate finite-sample bias arising from rare words.

After preprocessing the corpus, I estimate word embeddings for each party. With enough data, a good way to go about this might be to estimate the embeddings on our corpus separately for each party using artificial neural networks, a machine learning algorithm that underlies many of the recent developments in artificial intelligence.[10] Under this approach, the researcher trains the neural network to accomplish a predictive task: either predicting each word based on its context (the "continuous bag of words" model) or alternatively predicting the context based on the main word (the "skip-gram" model). *Id.* The weights generated by training the model are the dimensions for the word embeddings. [11] Unfortunately, the corpus here—though large by the standards of traditional legal scholarship—is small by machine learning standards.[12] Trying to locally estimate the embeddings in the traditional way is likely to yield low-quality representations of the

[10] *See* Tomas Mikolov et al., Efficient Estimation of Word Representations in Vector Space (2013), arXiv:1301.3781 [cs.CL] (providing such a method).

[11] *Id.*

[12] *See* Pedro L. Rodriguez, Arthur Spirling & Brandon M. Stewart, *Embedding Regression: Models for Context-Specific Description and Inference*, 117 AM. POL. SCI. REV. 1255, 1255 (2023) ("[T]raditional approaches generally require a lot of data to produce high-quality representations—that is, to produce embeddings that make sense and connote meaning of terms correctly.").

text.[13] Fortunately, recent innovations in machine learning provide a method of combining a smaller corpus with "pretrained" word embeddings obtained from a much larger corpus—such as Wikipedia or all Supreme Court cases—to give the words in the smaller corpus context-specific meaning.[14] To obtain an embedding for a word, this "à-la-carte" method considers the other words around it and effectively takes the average of the pretrained embeddings of those other words.[15] I employ this approach, using law-specific pretrained embeddings called "Law2Vec," which were estimated on a large corpus that includes (among other things) sixty-eight bound volumes of Supreme Court cases from 1998 to 2017 and fifty-four titles of the U.S. Code.[16] I use Law2Vec over other more general pretrained embeddings such as Word2Vec because legal vocabulary is specialized and lawyers often use words differently from laypersons. [17] Unlike the toy examples with only two dimensions, these pretrained embeddings have 200 dimensions (i.e., 200 different entries in each vector). After obtaining the pretrained embeddings and undertaking certain technical steps to further prepare the data for analysis, I estimate separate embeddings for each party.

Complete details on all these steps are contained in the `R` code made available with the Article.[18]

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[13] *See id.*

[14] Mikhail Khodak et al., *A La Carte Embedding: Cheap but Effective Induction of Semantic Feature Vectors*, *in* PROCEEDINGS OF THE 56TH ANNUAL MEETING OF THE ASSOCIATION FOR COMPUTATIONAL LINGUISTICS 12 (Iryna Gurevych & Yusuke Miya eds., 2018); Rodriguez, Spirling & Stewart, *supra* note 12.

[15] Rodriguez, Spirling & Stewart, *supra* note 12, at 1256 ("In a nutshell, the method takes embeddings that have been pretrained on large corpora (e.g., word2vec or GloVe embeddings readily available online), combined with a small sample of example uses for a focal word, and then induces a new context-specific embedding for the focal word.").

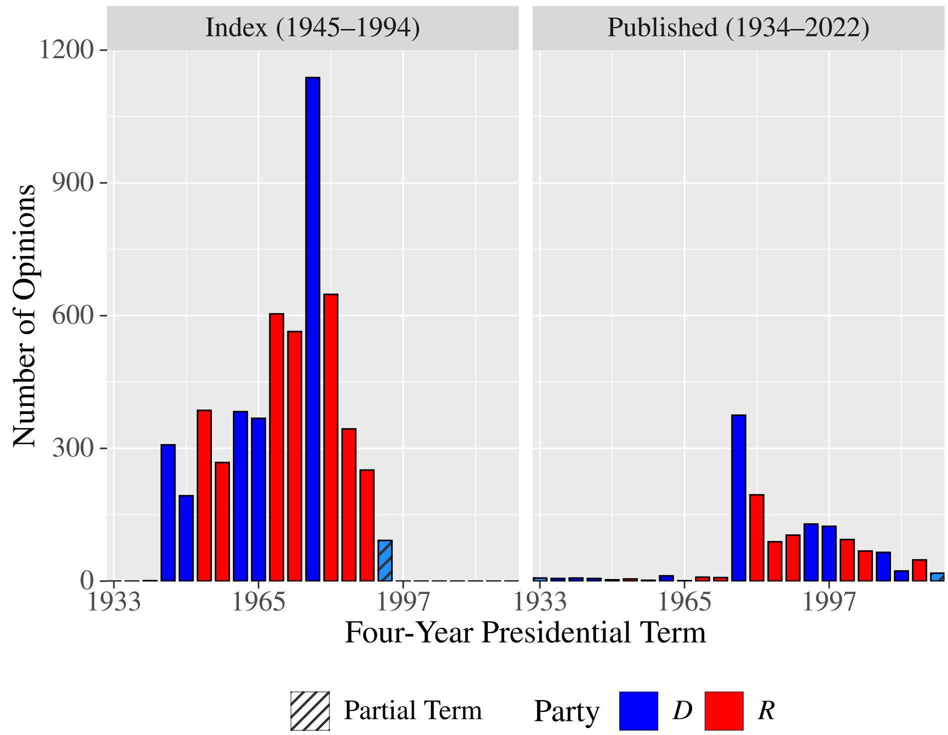
[16] Ilias Chalkidis & Dimitrios Kampas, *Deep Learning in Law: Early Adaptation and Legal Word Embeddings Trained on Large Corpora*, 27 ARTIFICIAL INTELLIGENCE & LAW 171 (2019).

[17] *See* Julian Nyarko & Sarath Sanga, *A Statistical Test for Legal Interpretation: Theory and Applications*, 38 J.L. ECON. & ORG. 539, 558–63 (2022) (finding that judges and laypersons use certain words differently).

[18] For additional implementation details, see Pedro L. Rodriguez, *Quick Start Guide*, *in* CONTEXT (GitHub repository, Aug. 4, 2023), https://github.com/prodriguezsosa/conText/blob/master/vignettes/quickstart.md.

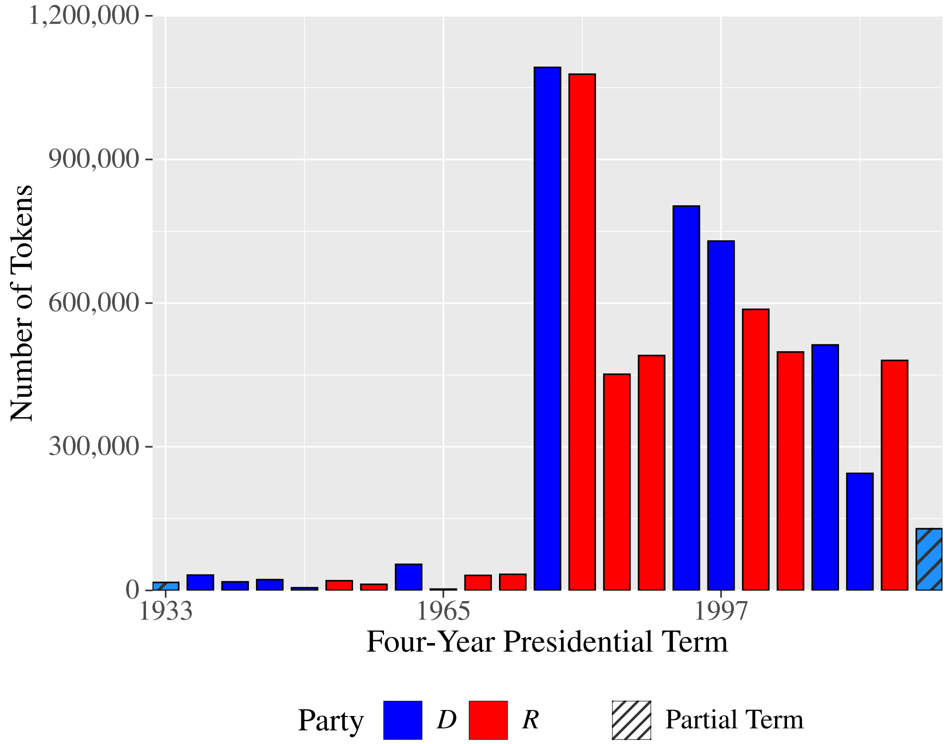
B. Supplemental Figures and Tables

FIGURE A1: NUMBER OF OLC OPINIONS BY PRESIDENTIAL TERM



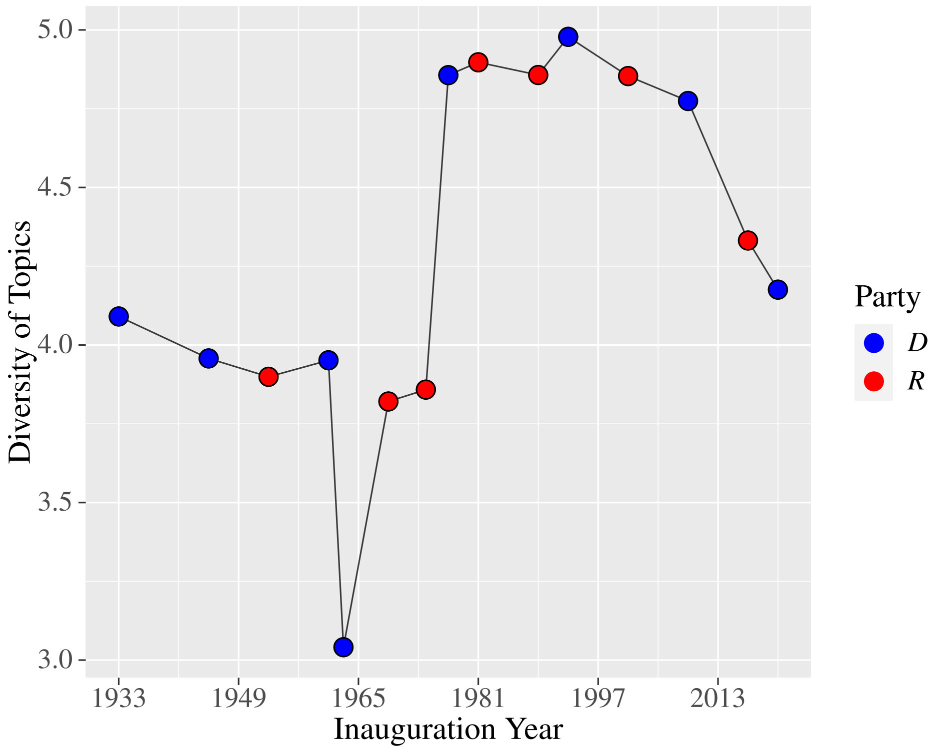
Note: The left-hand panel plots counts of opinions included in the index produced in the *Francis v. DOJ* litigation, and the right-hand panel plots counts of opinions scraped from the OLC website and included in the corpus. Presidential terms are defined in four-year increments starting in 1933. In the left-hand panel, the four-year terms starting in 1941 and 1993 are marked as partial because they do not include 1941–1944 (except a small portion of 1944) and 1995–1996, respectively. Additionally, the index does not include any opinions issued before 1945 or after 1994. In the right-hand panel, the four-year terms starting in 1933 and 2021 are marked as partial because they do not include 1933 and 2023–2024, respectively. Party refers to the political party of the sitting president.

FIGURE A2: NUMBER OF TOKENS IN OLC OPINIONS BY PRESIDENTIAL TERM



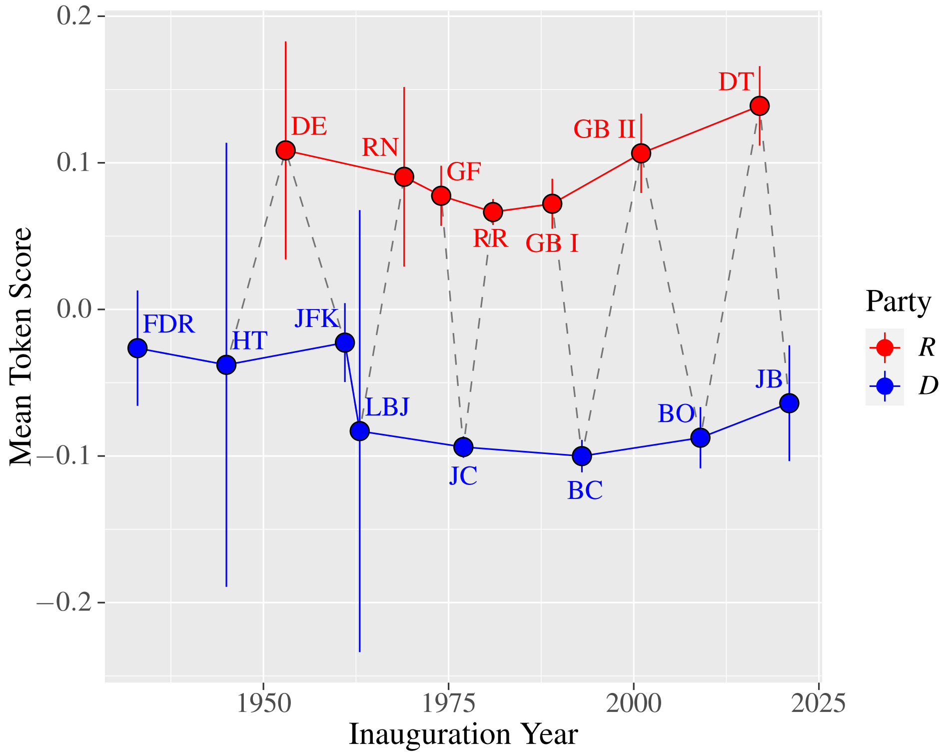
Note: The total number of tokens contained in the corpus is plotted for each four-year presidential term. The four-year terms starting in 1933 and 2021 are marked as partial because they do not include 1933 and 2023–2024, respectively. Party refers to the political party of the sitting president.

FIGURE A3: DIVERSITY OF TOPICS IN PUBLISHED OLC OPINIONS BY PRESIDENT



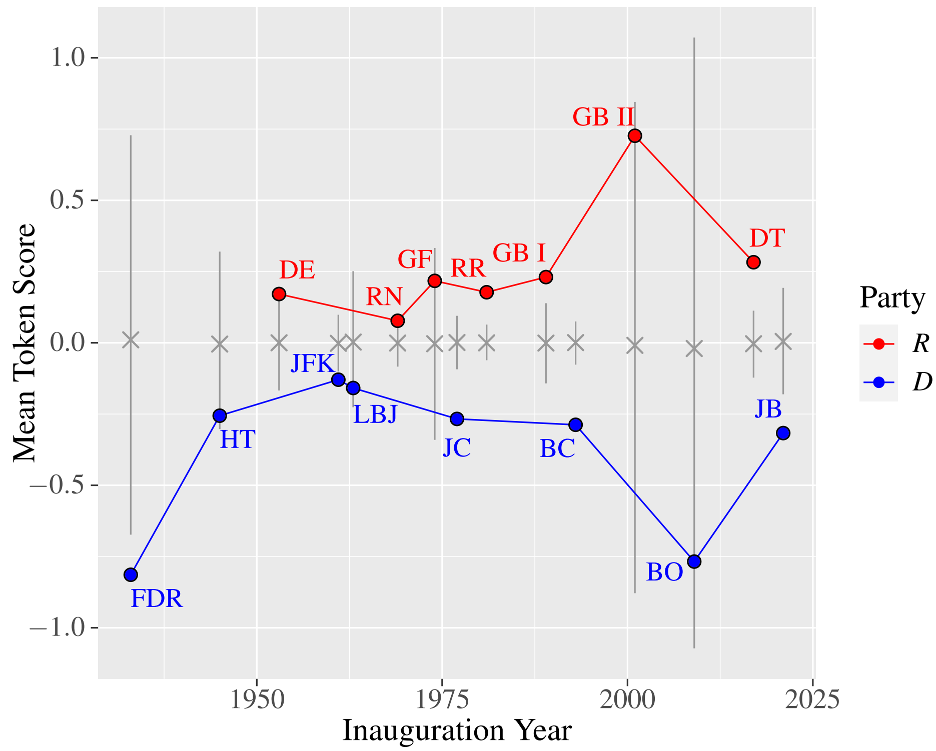
Note: Diversity of topics is defined as the empirical entropy for the mean distribution of topics in published opinions during the tenure of the relevant president. Formally, $Entropy_p = -\sum_t \overline{\pi}_{pt} \log_2(\overline{\pi}_{pt})$, where p indexes presidents, t indexes topics, and $\overline{\pi}_{pt}$ is defined as the mean topic proportion for topic t for all published opinions issued under president p.

FIGURE A4: AVERAGE TOKEN SCORE BY PRESIDENT (UNIGRAMS^{+})



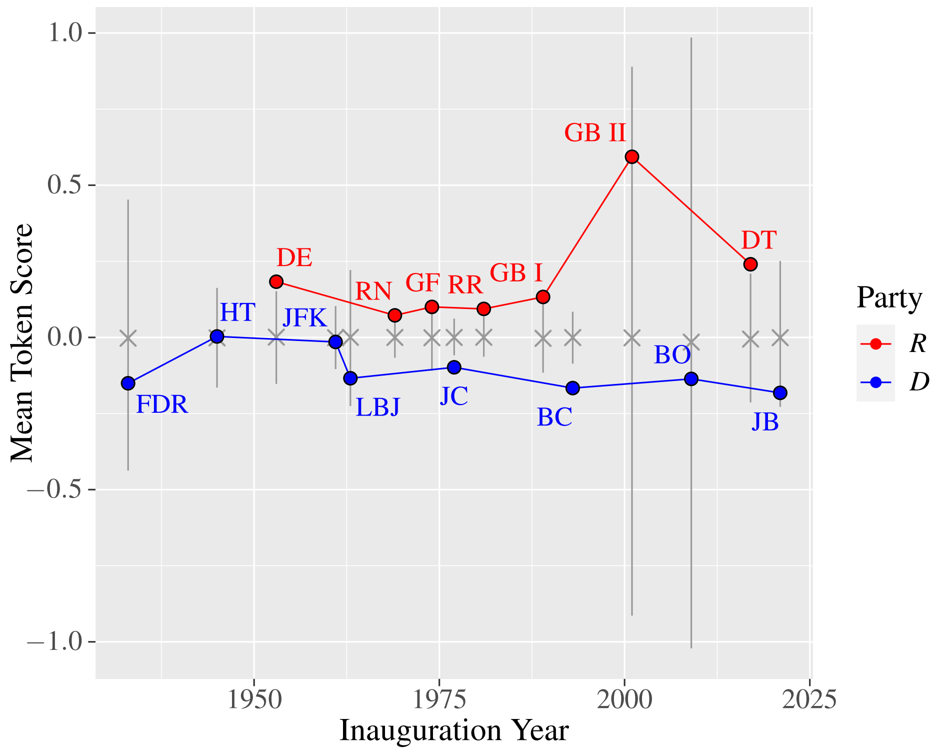
Note: Points are mean token scores for each president under the unigrams-plus tokenization, $\overline{\rho}_t^P$, where higher values indicate more use of Republican language. Vertical line segments are 95% confidence intervals, estimated using standard errors clustered by opinion. Party and initials respectively refer to the political party and name of the sitting president.

FIGURE A5: AVERAGE TOKEN SCORE BY PRESIDENT (BIGRAMS, LEAVE-OUT-TERM ROBUSTNESS CHECKS)



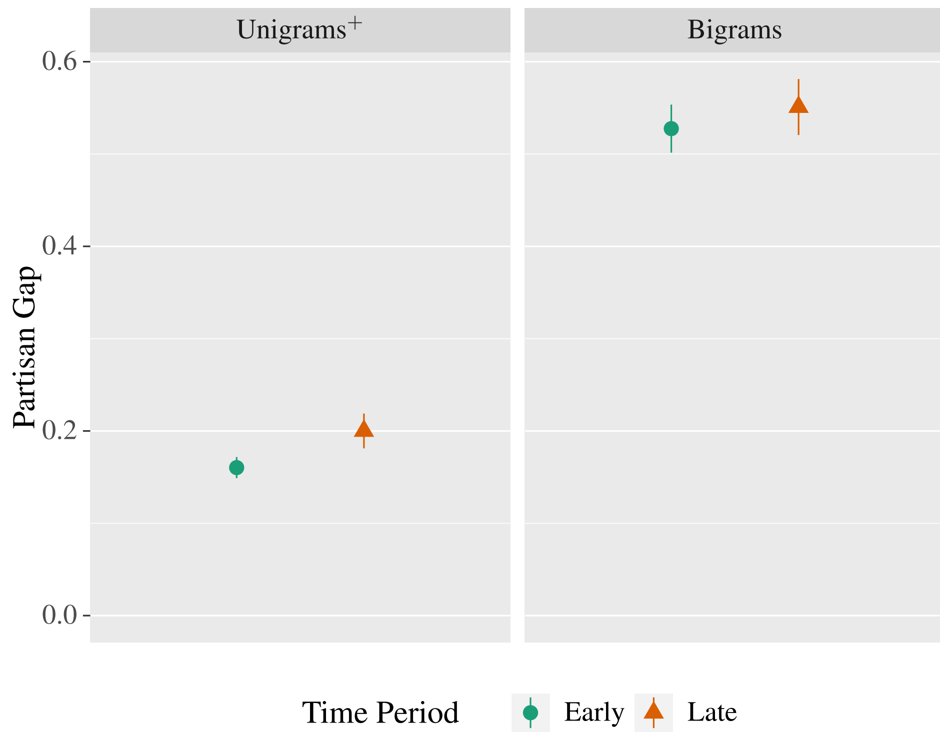
Note: Points are mean token scores for each president under the bigrams tokenization with four-year presidential terms left out during estimation, $\overline{\rho}_t^P$, where higher values indicate more use of Republican language. Grey $\times$'s and connected vertical lines are respectively means and 95% confidence intervals for permutation tests in which opinion party labels are randomly assigned with equal probability before estimation, using 1,000 permutations. Party and initials respectively refer to the political party and name of the sitting president.

FIGURE A6: AVERAGE TOKEN SCORE BY PRESIDENT (UNIGRAMS^{+}, LEAVE-OUT-TERM ROBUSTNESS CHECKS)



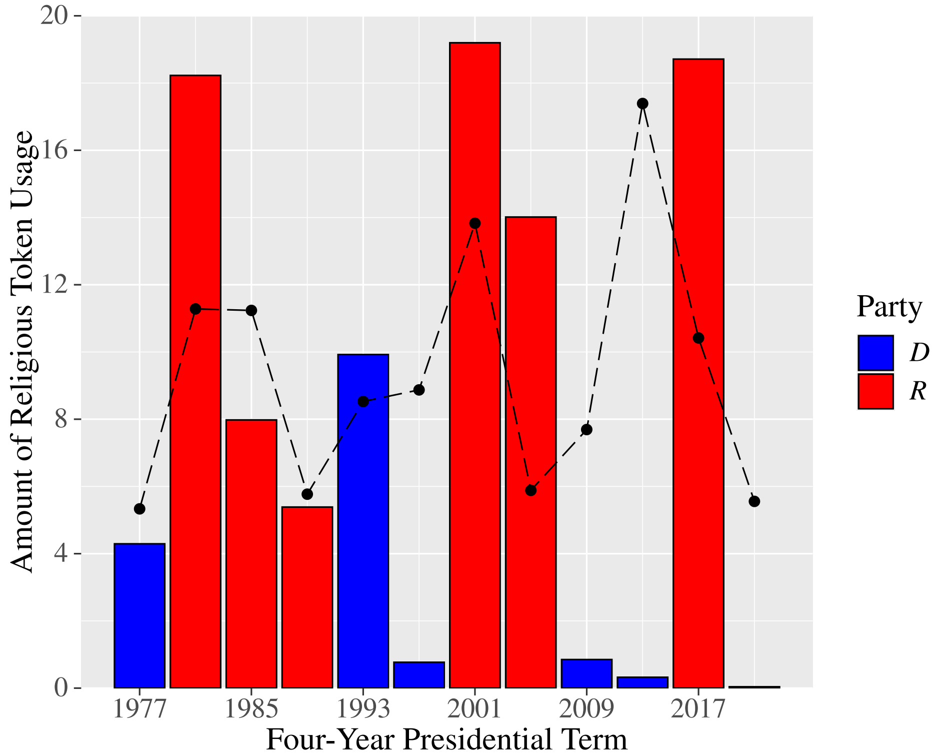
Note: Points are mean token scores for each president under the unigrams-plus tokenization with four-year presidential terms left out during estimation, $\overline{\rho}_t^P$, where higher values indicate more use of Republican language. Grey ×'s and connected vertical lines are respectively means and 95% confidence intervals for permutation tests in which opinion party labels are randomly assigned with equal probability before estimation, using 1,000 permutations. Party and initials respectively refer to the political party and name of the sitting president.

FIGURE A7: PARTISAN GAP BY TIME PERIOD, 1977–2022



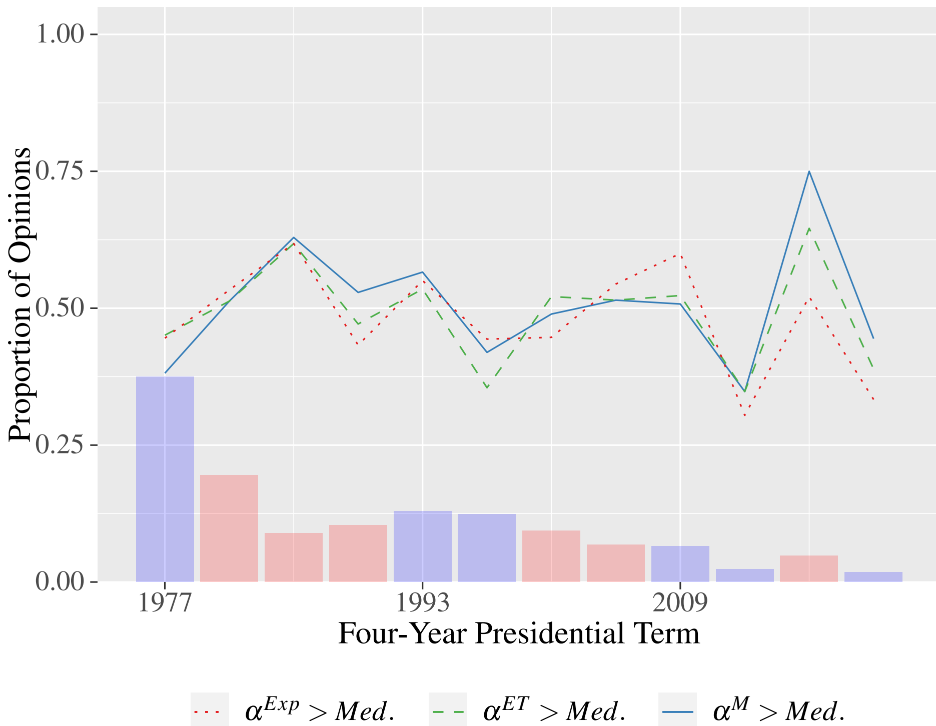
Note: The token-level partisan gap coefficient is plotted as a function of the time period. The coefficients are derived from estimating the linear regression model $\hat{\rho}_j = \beta_0 + \beta_1 Republican_j + \beta_2 Late_j + \beta_3(Republican_j \times Late_j) + \varepsilon_j$ for the 1977–2022 period, where j indexes tokens, $Republican_j$ is an dummy variable indicating whether token j was contained in an opinion issued under a Republican president, and $Late_j$ is a dummy variable indicating whether token j was contained in an opinion issued in 1989 or later. For each panel, the "early" point estimate is $\hat{\beta}_1$, and the "late" point estimate is $\hat{\beta}_1 + \hat{\beta}_3$. Vertical line segments are 95% confidence intervals, estimated using standard errors clustered by opinion.

FIGURE A8: USE OF RELIGIOUS TOKENS BY PRESIDENTIAL TERM, 1977–2022



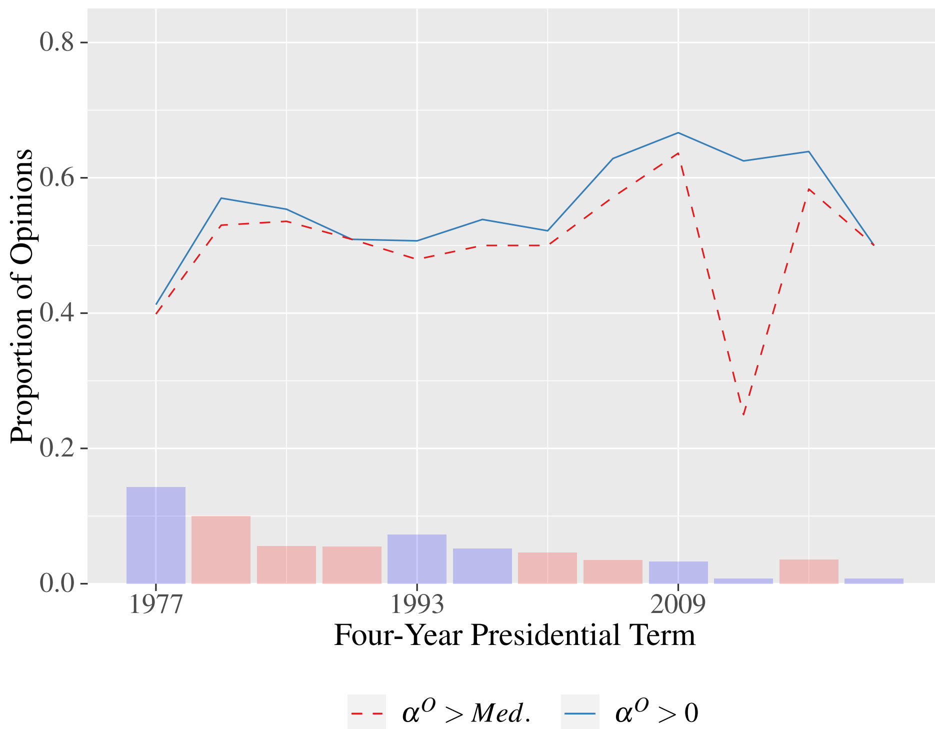
Note: Columns are standardized counts of religious token usage during each presidential term. Religions tokens include `religi`, `religion`, `church`, `religious freedom`, `establishment claus`, `religious organ`, `free exercise claus`, `freedom of religion`, `establishment of religion`, and `free exercis`. The counts are standardized to add up to 100 by dividing each count by the total number of religious tokens (2,469) and multiplying the result by 100. Points connected by dashed line segments are percentages of opinions that used a religious token. The final presidential term is a partial term, covering only 2021 and 2022.

FIGURE A9: PROPORTION OF CONSTITUTIONAL OPINIONS BY DICTIONARY AND PRESIDENTIAL TERM (HIGHER THRESHOLD FOR CONSTITUTIONAL LANGUAGE)



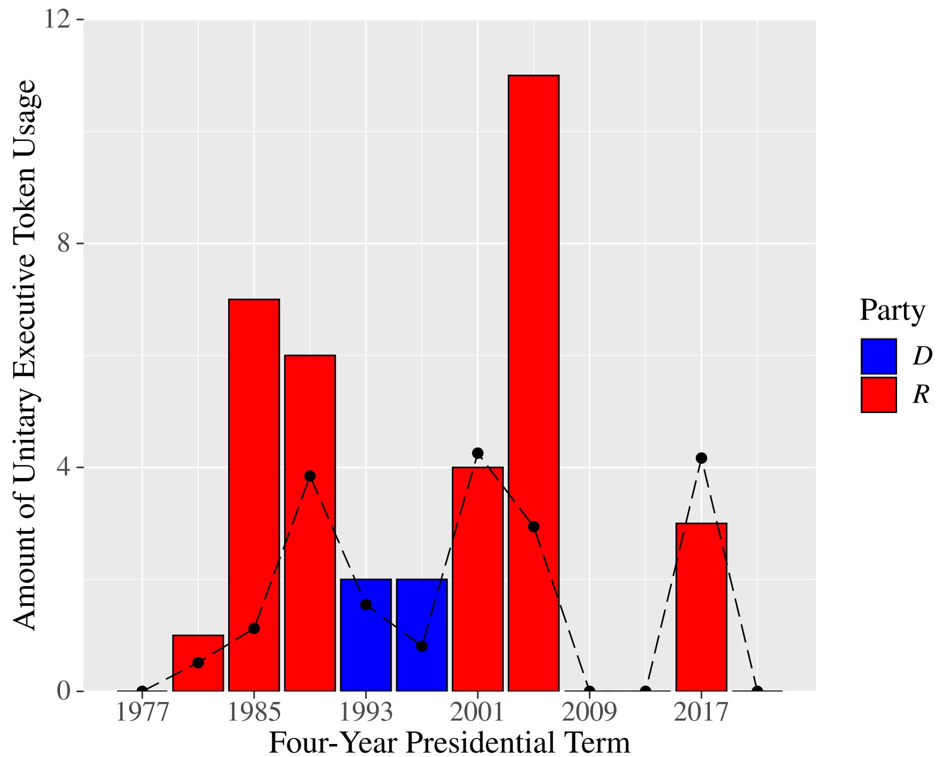
Note: The lines plot the proportion of opinions that contain constitutional language by dictionary and four-year presidential term. An opinion i is defined as containing constitutional language for dictionary d if $\alpha^d > \mathrm{med}(\alpha^d)$. M, ET, and Exp respectively refer to the minimal, textual extended, and expansive constitutional dictionaries. Columns are proportional to counts of the total number of opinions issued during the term (i.e., including both constitutional and nonconstitutional opinions).

FIGURE A10: PROPORTION OF CONSTITUTIONAL OPINIONS WITH ORIGINALISM LANGUAGE BY PRESIDENTIAL TERM (HIGHER THRESHOLD FOR CONSTITUTIONAL OPINIONS)



Note: Note: The lines plot the proportion of constitutional opinions with originalism language by presidential term. The solid line requires that the opinion contain a positive amount of originalism language, and the dashed line requires that the opinion contain more than the median amount of originalism language. Columns are proportional to counts of constitutional opinions issued during the term. Constitutional opinions are defined as those for which $\alpha^M > \text{med}(\alpha^M)$.

FIGURE A11: USE OF UNITARY EXECUTIVE TOKEN BY PRESIDENTIAL TERM, 1977–2022



Note: Columns are counts of unitary executive token usage during each presidential term. Points connected by dashed line segments are percentages of opinions that used the unitary executive token. The final presidential term is a partial term, covering only 2021 and 2022.

TABLE A1: CORPUS SUMMARY STATISTICS (OPINION LEVEL)

Variable	Mean	Median	St. Dev.	Min.	Max.
Tokens	5254.17	3664.50	5473.74	63.00	74357.00
Types	1070.87	918.00	701.70	44.00	6701.00
Sentences	188.44	128.00	197.69	3.00	2434.00
Tokens (Minimal)	8.70	1.00	21.87	0.00	300.00
Tokens (Textual)	17.38	6.00	35.19	0.00	753.00
Tokens (Textual Extended)	20.06	7.00	42.56	0.00	1003.00
Tokens (Originalism)	2.14	0.00	6.31	0.00	109.00
Tokens (Expansive)	42.75	23.00	71.87	0.00	1548.00
Tokens (Executive Power)	7.54	2.00	14.57	0.00	162.00
Republican President	0.44	0.00	0.50	0.00	1.00
Year	1989.55	1988.00	14.71	1934.00	2022.00

Note: Summary statistics for the OLC opinions corpus are reported. Tokens is the number of tokens in a document, including nonunique types, before any creation of compound tokens. Types is the number of unique types of different tokens in a document. Sentences is the number of sentences in a document. Tokens followed by parentheses are the number of tokens within the dictionary in parentheses (e.g., “Minimal” refers to the minimal constitutional dictionary). Republicant President is a dummary variable equal to 1 if the sitting president is a Republican. Year is the presidential year, defined as starting on January 20.

TABLE A2: OPINION TOPICS

Topic Label	Frequency	Most Likely Words (First Line) / Highest FREX Scores (Second Line)
Litigation involving federal officers and employees	6.41%	employe, interest, govern, depart, united_st, attorney, offici ethic, client, represent, attorney, former, lawyer, ausa
Agency rulemaking and administration	5.74%	agenc, legisl, provis, congress, cong, senat, requir sess, 1st, rept, cong, cargo, omb, rcra
Presidential authority and supervision of the executive branch	5.35%	execut, presid, power, constitut, congress, branch, author branch, execut, unconstitut, subordin, power, morrison, chadha
Presidential appointments and vacancies	4.58%	presid, offic, appoint, vacanc, term, senat, director vacanc, recess, reform, vacant, holdov, vice, nomin
Appropriations and expenditures	4.35%	appropri, fund, author, agenc, general, use, year gsa, gao, expenditur, comptrol, appropri, fiscal, antidefici
Regulatory boards and commissions	4.29%	board, commiss, member, agenc, author, feder, function board, commiss, chairperson, council, corpor, reorgan, chairman
Statutory interpretation	4.19%	section, statut, provis, congress, requir, interpret, read section, subsect, leas, confin, read, build, phrase
Congressional investigations of the executive branch	3.84%	presid, execut, committe, hous, privileg, inform, congression subpoena, privileg, subcommitte, white, oversight, document, testimoni
Federal personnel issues	3.48%	employe, servic, pay, employ, section, compens, feder contribut, hatch, leav, salari, compens, retir, hour
Federal courts	3.14%	court, case, right, constitut, 2d, crimin, rule trial, bankruptci, jeopardi, indict, doubl, impeach, wit
Federalism	3.05%	state, feder, law, author, court, united_st, local fugit, deput, marshal, arrest, polic, suicid, preemption
Agency litigation	2.9%	court, claim, action, agenc, feder, author, litig eeoc, complaint, reopen, settlement, suit, complain, croson
Presidential authority over foreign relations	2.8%	presid, foreign, treati, united_st, power, author, state treati, diplomat, negoti, diplomaci, china, nafta, withdraw
Federal funds	2.69%	fund, payment, tax, united_st, fee, treasuri, cost fslic, truste, prepay, levi, debt, ffb, payment
Access to agency information and records	2.67%	inform, record, agenc, disclosur, requir, public, use record, 552a, foia, feca, disclosur, secret, confidenti
Appointment of federal officers	2.59%	offic, appoint, claus, judg, united_st, court, posit appoint, judg, nomine, inferior, inelig, arbitr, rollback
Government investigations	2.57%	investig, inform, author, disclosur, general, intellig, depart oig, inspector, intellig, ig, grand, investig, disclosur
Presidential authority and the legislative process	2.54%	congress, bill, amend, constitut, veto, state, senat veto, pocket, adjourn, ratif, session, ratifi, legislatur
Property, money, and financial sanctions	2.36%	properti, bank, author, united_st, transfer, feder, reserv bank, iran, iranian, asset, fomc, ieepa, properti
Immigration	2.36%	alien, united_st, immigr, deport, remov, person, natur ina, alien, expatri, deport, immigr, citizenship, child
Presidential signing of legislation and writing-related issues	2.22%	presid, sign, print, offic, bill, memorandum, depart print, sign, signatur, gpo, affix, enrol, johnson
Individual rights (esp. speech, advertising, copyright)	2.21%	use, public, interest, inform, court, govern, protect copyright, advertis, lotteri, newspap, speech, airport, broadcast
Contractors, temporary workers, volunteers, veterans, abortions	2.18%	servic, postal, veteran, labor, va, abort, medic abort, veteran, usp, va, postal, wage, hyde
Gifts and payments to federal officials	2.09%	committe, advisori, tax, govern, return, foreign, emolu faca, smithsonian, acus, gift, emolu, advisori, nobel

TABLE A2: OPINION TOPICS (CONTINUED)

Topic Label	Frequency	Most Likely Words (First Line) / Highest FREX Scores (Second Line)
Foreign affairs and customs issues	2.07%	united_st, foreign, law, state, intern, author, nation passport, aircraft, custom, forfeitur, vessel, usg, seiz
Federally funded programs	1.94%	program, fund, grant, feder, educ, assist, school ura, colleg, school, nondiscrimin, hud, cdbg, educ
Native American and U.S. territory issues	1.93%	state, district, constitut, indian, congress, court, legisl indian, virgin, tribe, tribal, qui, tam, island
Commodities, infrastructure, and services	1.88%	requir, author, emerg, nation, contract, oil, energi bid, petroleum, oil, hubzon, export, energi, quota
Presidential authority and military force	1.84%	presid, forc, war, author, united_st, militari, use unscr, blockad, iraq, kosovo, wpr, hostil, troop
Miscellaneous federal agency issues	1.81%	agreement, author, epa, air, employe, feder, agenc epa, polygraph, clean, air, nasa, carrier, opm
Criminal law	1.71%	crimin, offens, crime, convict, penalti, court, punish convict, pardon, punish, victim, death, offens, penalti
Military law	1.66%	militari, law, defens, civilian, arm, forc, author comitatus, poss, dod, civilian, gc4, militari, armi
Federal lands and waters	1.27%	right, land, state, water, feder, law, united_st water, forest, militia, land, easement, monument, coastal
Surveillance and privacy	1.2%	communic, use, surveil, search, privaci, united_st, electron einstein, surveil, fisa, intercept, telephon, electron, comput
Religion	1.07%	religi, religion, court, govern, claus, establish, church peyot, rfra, religi, secular, church, religion, nac
Miscellaneous policy-related issues (esp. census, FDA, sports)	1.03%	census, use, secretari, fda, claus, loan, sport bet, wager, rodeo, sport, census, fda, vaccin

Note: Topics are generated by a topic model fit with $K = 37$ and spectral initialization. Labels are supplied by the researcher. Frequency is the mean topic proportion, expressed as a percentage. Most likely words are the words within the topic with the highest probability. Words with highest FREX are the words with the highest frequency–exclusivity scores, as defined by Margaret E. Roberts, Brandon M. Stewart, and Dustin Tingley, *stm: An R Package for Structural Topic Models*, 91 J. STAT. SOFT. 1 (2019). The topic capturing typographical errors is omitted.

TABLE A3: META-TOPIC CATEGORY ASSIGNMENTS

Topic Label	Meta-Topic Category
Agency rulemaking and administration	Administrative agencies
Regulatory boards and commissions	Administrative agencies
Federal personnel	Administrative agencies
Access to agency information and records	Administrative agencies
Government investigations	Administrative agencies
Miscellaneous federal agency issues	Administrative agencies
Appropriations and expenditures	Appropriations, expenditures, and funds
Federal funds	Appropriations, expenditures, and funds
Federally funded programs	Appropriations, expenditures, and funds
Litigation involving federal employees	Courts and litigation
Federal courts	Courts and litigation
Agency litigation	Courts and litigation
Federalism	Federalism, tribes, and territories
Native American and U.S. territory issues	Federalism, tribes, and territories
Presidential authority over foreign affairs	Foreign affairs
Foreign affairs and customs issues	Foreign affairs
Presidential authority and military force	Foreign affairs
Military law	Foreign affairs
Property, money, and financial sanctions	Miscellaneous
Presidential signing of legislation and writing-related issues	Miscellaneous
Gifts and payments to federal officials	Miscellaneous
Commodities, infrastructure, and services	Miscellaneous
Federal lands and waters	Miscellaneous
Presidential authority and supervision of the executive branch	Separation of powers
Presidential appointments and vacancies	Separation of powers
Congressional investigations of the executive branch	Separation of powers
Appointment of federal officers	Separation of powers
Presidential authority and the legislative process	Separation of powers
Statutory interpretation	Statutory interpretation
Immigration	Substantive law and policy
Individual rights (esp. speech, information, advertising, and copyright)	Substantive law and policy
Contractors, temporary workers, volunteers, veterans, and abortions	Substantive law and policy
Criminal law	Substantive law and policy
Surveillance and privacy	Substantive law and policy
Religion	Substantive law and policy
Misc. policy-related issues (esp. census, food and drug, and sports)	Substantive law and policy

Note: Topics are assigned by the researcher to meta-topic categories.

TABLE A4: NAIVE BAYES CLASSIFIER PERFORMANCE BY PARTY

Tokenization	Accuracy (*D*)	Accuracy (*R*)
Unigrams	0.69	0.53
Unigrams$^+$	0.69	0.55
Bigrams	0.72	0.58

Note: Accuracy of the naive Bayes classifier by party of the sitting president is reported. Tokenizations follow those reported in Table 2.

TABLE A5: NAIVE BAYES CLASSIFIER PERFORMANCE (STATES OF THE UNION)

Tokenization	Accuracy	F_1 (Positive Event = *D*)	F_1 (Positive Event = *R*)
Unigrams	0.81	0.83	0.79
Unigrams$^+$	0.81	0.83	0.79
Bigrams	0.90	0.90	0.90

Note: Performance of the naive Bayes classifier on the State of the Union corpus from 1934–2022 is reported. Tokenizations and metrics follow those reported in Table 2.

TABLE A6: PARTISAN GAP BY TIME PERIOD, 1977–2022

	$\hat{\rho}_j$ (Unigrams$^+$)	$\hat{\rho}_j$ (Bigrams)
Republican President	0.16^{***}	0.53^{***}
	(0.01)	(0.01)
Late	-0.00	0.01
	(0.01)	(0.01)
Republican President × Late	0.04^{***}	0.02
	(0.01)	(0.02)

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Note: Linear regressions are estimated over the 1977–2022 period with the individual token as the unit of analysis. The dependent variable, $\hat{\rho}_j$, is the token-level partisan tilt score, with higher values reflecting a more Republican token. *Republican President* is a dummy variable indicating whether the president is a Republican. *Late* is a dummy variable indicating whether the opinion was issued in 1989 or later. Standard errors clustered by opinion are in parentheses. Intercepts are omitted from the table for ease of presentation.

TABLE A7: MOST PARTISAN TOKENS AMONG MOST INFLUENTIAL TOKENS (UNIGRAMS$^+$)

Most Democratic				Most Republican			
Token	$\hat{\rho}_j$	n_j	$\hat{\rho}_j n_j$	Token	$\hat{\rho}_j$	n_j	$\hat{\rho}_j n_j$
rept	−4.41	250	−1103.75	unscr	5.03	274	1379.55
csrdf	−3.93	89	−350.14	dni	4.31	113	486.69
acus	−3.83	132	−506.22	prepay	3.11	139	432.66
cfr	−3.20	230	−735.60	deliberative process	2.61	124	324.23
fair us	−3.07	153	−469.37	al qaeda	2.56	129	329.95
usp	−2.97	392	−1162.44	block grant	2.50	192	479.32
ssa	−2.90	221	−640.28	interpol	2.48	159	394.79
einstein	−2.89	316	−914.00	religious organ	2.42	149	359.88
annuiti	−2.83	121	−342.41	militia	2.38	549	1307.93
fisheri	−2.42	183	−443.39	ffb	2.24	207	462.71
puerto rico	−2.18	159	−346.22	fslic	2.19	244	534.75
virgin island	−2.13	216	−460.60	armed conflict	2.19	242	529.10
trust fund	−2.06	219	−451.48	posse comitatus	1.99	333	663.98
census	−1.99	426	−849.26	religi	1.85	878	1620.20
nasa	−1.98	344	−679.48	marijuana	1.83	175	319.64
territorial sea	−1.76	244	−429.74	nic	1.72	193	331.47
iranian	−1.67	242	−403.26	terrorist	1.64	271	445.41
blockad	−1.50	219	−328.44	executive privileg	1.58	1010	1591.66
opm	−1.45	996	−1440.21	passport	1.47	292	429.79
carrier	−1.29	357	−461.75	church	1.46	333	487.47
popul	−1.27	254	−323.76	controlled subst	1.42	226	321.70
copyright	−1.25	246	−307.95	contempt	1.38	394	543.08
antidefici	−1.17	316	−369.08	iraq	1.37	687	942.55
oig	−1.16	433	−501.16	faith	1.36	236	320.70
departm	−1.04	320	−332.96	pocket veto	1.34	315	422.56
victim	−0.94	329	−308.99	establishment claus	1.32	299	395.56
iran	−0.90	567	−512.15	dea	1.31	306	400.49
columbia	−0.81	832	−674.30	subpoena	1.28	925	1188.48
federal employe	−0.80	704	−564.59	res	1.28	697	891.78
contribut	−0.78	802	−628.40	religion	1.22	588	717.13

Note: Summary statistics are reported for the most partisan tokens among those tokens with the highest aggregate contribution to the overall partisan gap. $\hat{\rho}_j$ is the average token-level partisan tilt score under the extended unigrams tokenization, with higher values reflecting a more Republican token. n_j is the number of times the token appears in the corpus. $\hat{\rho}_j n_j$ thus captures the aggregate influence of the token on the overall partisan gap. For the 150 tokens with the lowest (highest) $\hat{\rho}_j n_j$ values, the thirty most Democratic (Republican) tokens are reported on the left (right).

TABLE A8: MOST PARTISAN TOKENS AMONG MOST INFLUENTIAL TOKENS (BIGRAMS)

Most Democratic				Most Republican			
Token	$\hat{\rho}_j$	n_j	$\hat{\rho}_j n_j$	Token	$\hat{\rho}_j$	n_j	$\hat{\rho}_j n_j$
rept 95th	−3.97	53	−210.18	rep 97th	4.12	67	275.88
titl rule	−3.86	107	−413.15	fy ndaa	3.49	48	167.35
oblig advanc	−3.80	51	−193.60	religi school	3.04	53	161.15
sess rept	−3.54	34	−120.25	enforc file	3.02	68	205.27
district claus	−3.48	64	−222.61	geneva convent	2.89	104	301.00
offici guest	−3.40	57	−193.78	substanti burden	2.86	78	222.96
liabil insur	−3.38	38	−128.42	materi breach	2.85	110	313.38
foreign air	−3.27	39	−127.52	north church	2.64	54	142.57
restrict competit	−3.13	43	−134.56	investig file	2.64	69	182.13
fair use	−3.08	160	−492.72	assassin record	2.64	56	147.69
nongovernment member	−2.91	44	−128.21	old north	2.64	57	150.31
debt limit	−2.89	117	−337.60	design director	2.63	70	183.80
judgment claus	−2.87	67	−192.14	block grant	2.58	255	659.16
resid requir	−2.80	81	−226.82	custom servic	2.56	86	219.97
impeach judgment	−2.77	73	−202.25	al qaeda	2.53	128	323.81
contribut polit	−2.74	44	−120.41	former counsel	2.53	65	164.34
veteran prefer	−2.70	77	−207.69	religi activ	2.48	104	257.80
census inform	−2.68	62	−165.92	doc res	2.46	82	201.82
train servic	−2.66	49	−130.31	terrorist attack	2.44	85	207.34
public debt	−2.65	90	−238.35	crimin contempt	2.41	119	287.20
action program	−2.63	96	−252.76	religi organ	2.41	150	360.92
doubl jeopardi	−2.59	156	−404.12	97th cong	2.39	99	237.01
access doj	−2.49	51	−126.82	doctrin execut	2.34	62	144.82
nonimmigr alien	−2.48	67	−166.18	delib process	2.31	166	383.13
composit claus	−2.46	63	−155.19	res doc	2.31	72	166.12
mr justic	−2.36	63	−148.90	religi institut	2.30	83	191.22
fiduciari oblig	−2.32	65	−150.97	foreign entiti	2.23	137	305.71
appropri white	−2.30	69	−158.82	religi belief	2.22	90	199.85
polit contribut	−2.24	72	−161.52	exercis claus	2.19	113	247.56
virgin island	−2.23	251	−560.91	arm conflict	2.17	243	527.54

Note: Summary statistics are reported for the most partisan tokens among those tokens with the highest aggregate contribution to the overall partisan gap. $\hat{\rho}_j$ is the average token-level partisanship score under the bigrams tokenization, with higher values reflecting a more Republican opinion. n_j is the number of times the token appears in the corpus. $\hat{\rho}_j n_j$ thus captures the aggregate influence of the token on the overall partisan gap. For the 150 tokens with the lowest (highest) $\hat{\rho}_j n_j$ values, the thirty most Democratic (Republican) tokens are reported on the left (right).

TABLE A9: PARTISAN GAP BY PERIOD, 1977–2022 (CONSTITUTIONAL TOKENS)

	$\hat{\rho}_j$	$\hat{\rho}_j$
Republican President	0.25^{***}	0.23^{***}
	(0.03)	(0.04)
Late		−0.00
		(0.03)
Republican President × Late		0.03
		(0.06)

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$

Note: Linear regressions are estimated over the 1977–2022 period with the individual token as the unit of analysis, limiting the sample to tokens contained in the expansive constitutional dictionary. The dependent variable, $\hat{\rho}_j$, is the token-level partisan tilt score, with higher values reflecting a more Republican token. *Republican President* is a dummy variable indicating whether the president is a Republican. *Late* is a dummy variable indicating whether the opinion was issued in 1989 or later. Standard errors clustered by opinion are in parentheses. Intercepts are omitted from the table for ease of presentation.

TABLE A10: OPINION-LEVEL PARTISAN GAP AND TOPIC CHOICE, 1977–2022

	$\hat{\rho}_i$	$\hat{\rho}_i$	$\hat{\rho}_i$	$\hat{\rho}_i$
Republican President	0.12^{***}	0.07^{***}	0.12^{***}	0.10^{***}
	(0.02)	(0.01)	(0.02)	(0.01)
Time	0.00^{*}	0.00^{**}	0.00^{**}	0.00^{***}
	(0.00)	(0.00)	(0.00)	(0.00)
Republican President × Time			−0.00	-0.00^{+}
			(0.00)	(0.00)
Topic fixed effects		✓		✓

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$

Note: Linear regressions are estimated over the 1977–2022 period under the bigrams tokenization with the individual opinion as the unit of analysis. The dependent variable, $\hat{\rho}_i$, is the average token-level partisan tilt score for all tokens in the opinion, with higher values reflecting a more Republican opinion. *Republican President* is a dummy variable indicating whether the president is a Republican. *Time* is a linear time trend, with $Time = 0$ in 1977. For topic fixed effects, the topic for a document is the topic with the highest topic proportion for the document. Standard errors clustered by topic are in parentheses. Intercepts are omitted from the tables for ease of presentation.

TABLE A11: PARTISAN GAP BY OPINION TYPE, 1977–2022

	$\hat{\rho}_j$ (Unigrams$^+$)	$\hat{\rho}_j$ (Bigrams)
Republican President	0.16^{***}	0.50^{***}
	(0.01)	(0.01)
Constitutional	0.03^{***}	0.05^{***}
	(0.01)	(0.01)
Republican President × Constitutional	0.03^{*}	0.04^{*}
	(0.01)	(0.02)

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Note: Linear regressions are estimated over the 1977–2022 period with the individual token as the unit of analysis. The dependent variable, $\hat{\rho}_j$, is the token-level partisan tilt score, with higher values reflecting a more Republican token. *Republican President* is a dummy variable indicating whether the president is a Republican. *Constitutional* is a dummy variable indicating whether the opinion contains the word "constitution" or variants thereof. Standard errors clustered by opinion are in parentheses. Intercepts are omitted from the table for ease of presentation.

TABLE A12: PARTISAN USE OF MINIMAL CONSTITUTIONAL LANGUAGE OVER TIME, 1977–2022

	$\alpha^M > 0$	$\alpha^M > 0$	$\alpha^M > 0$	$\alpha^M > 0$
Republican President	1.77***		1.66***	1.90***
	(0.20)		(0.19)	(0.34)
Time		1.02***	1.02***	1.03***
		(0.00)	(0.00)	(0.01)
Republican President × Time				0.99
				(0.01)

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Note: Logistic regressions are estimated over the 1977–2022 period with the individual opinion as the unit of analysis. α^M is defined as the proportion of tokens in the minimal constitutional dictionary, so the dependent variable, $\alpha^M > 0$, is a dummy variable indicating whether the opinion contains any tokens in the minimal constitutional dictionary. *Republican President* is a dummy variable indicating whether the president is a Republican. *Time* is a linear time trend, with *Time* $= 0$ in 1977. Coefficients are odds ratios. Robust standard errors (HC3) are in parentheses.

TABLE A13: PARTISAN USE OF ORIGINALISM LANGUAGE OVER TIME, CONSTITUTIONAL SUBCORPUS, 1977–2022

	$\alpha^O > 0$	$\alpha^O > 0$	$\alpha^O > 0$	$\alpha^O > 0$
Republican President	1.20		1.16	1.69*
	(0.17)		(0.17)	(0.40)
Time		1.02***	1.02***	1.03***
		(0.01)	(0.01)	(0.01)
Republican President × Time				0.98*
				(0.01)

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.

Note: Logistic regressions are estimated over the 1977–2022 period with the individual opinion as the unit of analysis for the subcorpus of opinions for which $\alpha^M > 0$. α^O is defined as the proportion of tokens in the originalism dictionary, so the dependent variable, $\alpha^O > 0$, is a dummy variable indicating whether the opinion contains any tokens in the originalism dictionary. *Republican President* is a dummy variable indicating whether the president is a Republican. *Time* is a linear time trend, with *Time* $= 0$ in 1977. Coefficients are odds ratios. Robust standard errors (HC3) are in parentheses.

TABLE A14: PARTISAN USE OF EXECUTIVE POWER LANGUAGE OVER TIME, 1977–2022

	$\alpha^{EP} > 0$	$\alpha^{EP} > 0$	$\alpha^{EP} > 0$	$\alpha^{EP} > 0$
Republican President	1.83^{***}		1.65^{***}	1.91^{**}
	(0.24)		(0.22)	(0.38)
Time		1.04^{***}	1.04^{***}	1.04^{***}
		(0.01)	(0.01)	(0.01)
Republican President × Time				0.99
				(0.01)

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$

Note: Logistic regressions are estimated over the 1977–2022 period with the individual opinion as the unit of analysis. α^{EP} is defined as the proportion of tokens in the executive power dictionary, so the dependent variable, $\alpha^{EP} > 0$, is a dummy variable indicating whether the opinion contains any tokens in the executive power dictionary. *Republican President* is a dummy variable indicating whether the president is a Republican. *Time* is a linear time trend, with $Time = 0$ in 1977. Coefficients are odds ratios. Robust standard errors (HC3) are in parentheses.

TABLE A15: OPINIONS WITH THE MOST DISTINCTIVELY REPUBLICAN AND DEMOCRATIC EXECUTIVE POWER CONTEXTS

Republican Presidents		
Title	Date	President
Congressional Requests for Confidential Executive Branch Information	June 19, 1989	George H.W. Bush
Testimonial Immunity Before Congress of the Former Counsel to the President	May 20, 2019	Donald J. Trump
Constitutionality of the OLC Reporting Act of 2008	Nov. 14, 2008	George W. Bush
Attempted Exclusion of Agency Counsel from Congressional Depositions of Agency Employees	May 23, 2019	Donald J. Trump
Prosecution for Contempt of Congress of an Executive Branch Official Who Has Asserted a Claim of Executive Privilege	May 30, 1984	Ronald Reagan
Democratic Presidents		
Title	Date	President
Authority of the President to Designate Another Member as Chairman of the Federal Power Commission	Feb. 28, 1961	John F. Kennedy
Presidential Authority Under the Trade Expansion Act to Adjust Shipments of Oil to and from Puerto Rico	Feb. 6, 1980	Jimmy Carter
Continuing Service of Deputy Director of OMB as Acting Director During Vacancy	Dec. 22, 1977	Jimmy Carter
Access to Classified Information	Nov. 26, 1996	William J. Clinton
Authority to Employ White House Officials Exempt from Annual and Sick Leave Act During Appropriations Lapse	Apr. 8, 2011	Barack Obama

Note: For each party, five opinions with the most distinctive executive power contexts are listed. The opinions are identified as follows: (1) identify all contexts around the executive power terms, calculate the cosine similarity between the context and each party-specific executive power embedding, and take the ratio of the Republican cosine similarity to the Democratic cosine similarity; (2) for each party, exclude contexts that are in the bottom 75% cosine similarity to the party-specific embedding; (3) identify the opinions associated with each context; and (4) for each party, identify the five opinions issued under that party with the highest (for Republicans) or lowest (for Democrats) context similarity ratios.

TABLE A16: EXECUTIVE POWER LANGUAGE AND AUTHORITARIANISM (EXCLUDING OPINIONS ISSUED UNDER GEORGE W. BUSH)

Closer to Democratic Embedding		Closer to Republican Embedding			
Word	Partisanship Ratio	Word	Partisanship Ratio	Word	Partisanship Ratio
		punish	6.18***	protect	1.15***
		domin	1.77***	command	1.15***
		enforc	1.69***	sediti	1.14***
		coerc	1.59***	disloyalti	1.14***
		apprehend	1.52***	loyal	1.14***
		stabil	1.50***	weapon	1.14***
		assault	1.45***	troop	1.14***
		rebellion	1.39***	violent	1.14***
		insurrect	1.39***	militia	1.13***
		disobedi	1.37***	unilater	1.13***
		hostil	1.37***	homeland	1.13***
		imprison	1.36***	sovereign	1.12***
		forcibli	1.36***	terror	1.12***
		fight	1.33***	revolt	1.12***
		disciplinari	1.30***	unitari	1.12***
		riot	1.27***	violenc	1.11***
		surveil	1.27***	sacrific	1.11***
		tortur	1.26***	sedit	1.11***
		mercenari	1.26***	patriot	1.11***
		fighter	1.24***	war	1.09***
		central	1.22***	order	1.08***
		vigil	1.21***	author	1.07***
		polic	1.21***	gun	1.07***
		complianc	1.21***	forcibl	1.06***
		treason	1.21***	armi	1.05***
		allegi	1.21***	battl	1.05***
		disciplin	1.21***	prison	1.04***
		paramilitari	1.19***	duti	1.03**
		disloy	1.18***	tradit	1.03*
		defens	1.18***	secur	1.03*
		murder	1.18***	forc	1.03***
		power	1.17***	militari	1.03***
		terrorist	1.17***	navi	1.03***
		jail	1.16***	soldier	1.03***
		loyalti	1.16***	moral	1.03+
		coercion	1.16***	decre	1.03*
		combat	1.16***	firearm	1.01

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; + $p < 0.1$

TABLE A17: EXECUTIVE POWER LANGUAGE AND AUTHORITARIANISM (EXCLUDING FOREIGN POLICY OPINIONS)

Closer to Democratic Embedding		Closer to Republican Embedding			
Word	Partisanship Ratio	Word	Partisanship Ratio	Word	Partisanship Ratio
allegi	0.93	punish	4.71***	coercion	1.15***
secur	0.96*	domin	2.29***	disciplinari	1.15***
forc	0.99	coerc	2.24***	combat	1.15***
decre	0.99	enforc	1.71***	weapon	1.15***
		apprehend	1.64***	loyalti	1.14***
		assault	1.62***	complianc	1.14***
		imprison	1.43***	troop	1.14***
		hostil	1.41***	militia	1.12***
		rebellion	1.39***	paramilitari	1.12***
		fight	1.37***	loyal	1.12***
		forcibli	1.35***	patriot	1.12***
		insurrect	1.34***	unitari	1.11***
		murder	1.33***	violenc	1.10***
		mercenari	1.30***	author	1.10***
		sediti	1.30***	homeland	1.09***
		sedit	1.29***	revolt	1.09***
		tortur	1.28***	sovereign	1.09***
		vigil	1.28***	unilater	1.08***
		surveil	1.26***	war	1.08***
		disloy	1.25***	disloyalti	1.07***
		treason	1.25***	terror	1.05***
		polic	1.24***	sacrific	1.05**
		riot	1.23***	duti	1.05**
		disobedi	1.20***	militari	1.04***
		central	1.20***	tradit	1.04*
		defens	1.19***	forcibl	1.04***
		protect	1.18***	gun	1.04***
		jail	1.18***	navi	1.04***
		command	1.18***	battl	1.03*
		stabil	1.18***	moral	1.02
		fighter	1.16***	order	1.02*
		disciplin	1.16***	soldier	1.02**
		violent	1.16***	firearm	1.02*
		power	1.16***	prison	1.01
		terrorist	1.16***	armi	1.01

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$