Supporting Information for

Motivated Reasoning in the Field: Polarization of Prose, Precedent, and Policy in U.S. Circuit Courts, 1891-2013

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This PDF file includes:

Supporting Information Text

This document contains additional information on training details of classification tasks, validation checks, and additional analyses.

Training

Text Classification. We implement fine-tuning on three popular transformer-based pre-trained models and use a simple average ensemble of predictions as the final predictions of texts on political affiliations of judges. The first model we use is DistilBERT (1), a smaller version of the BERT model designed to overcome the slow training problem of BERT (2) due to the large model size while obtaining similar performance as BERT. Secondly, we use two improved version of BERT, XLnet (3) and twitter-RoBERTa (4) that are trained on larger corpus and with improved architecture than the original BERT model.

For fine-tuning, we used the Python package `transformer` and accessed pre-trained models from Huggingface.co, a collaborative open-source platform for model sharing. The `distilbert-base-uncased-finetuned-sst-2-english` model was fine-tuned using default parameters over five epochs on 70% of a 10% sample (comprising 22,922 opinions), with the remainder serving as the test set. The `xlnet-base-cased` and `twitter-roberta-base-sentiment-latest` models were trained on 70% of a 5% sample for five epochs with a learning rate of 2e-5, other parameters being default, due to computational limitations. Post fine-tuning, these models were applied to the entire sample for political party predictions.

Overall, three models exhibited comparable results, consistently achieving a prediction accuracy around 0.7, shown in Table S1. Altering the number of epochs from two to eight did not significantly impact the outcomes, as we consistently employed the best model for predictions.

Table S1. Model Performance Metrics, Text Classification

Model	Training Loss	Validation Loss	Accuracy	N
DistilBERT	0.5013	0.5481	0.707588	22,292
twitter-RoBERTa	0.4897	0.5960	0.700084	11,146
XLnet	0.4740	0.5926	0.698619	11,146

Citation Classification. We first use a grid search method with K-fold cross validation to tune the parameters used in different algorithms (a list of commonly used algorithms) in order to maximize the evaluation metric of that algorithm (here we used the AUC score). Then we use a voting ensemble method based on the best estimator of each model to average results obtained from the set of algorithms. The analysis is done using Python packages `scikit-learn` and `xgboost`. After training, we apply the ensemble model on full sample.

For each algorithm, we allow the algorithm to search among a set of possible parameters to optimize the prediction, as in (5):

- Elastic Net. A10-fold cross validation is added to the algorithm to choose the optimal mixing parameter of LASSO and ridge regression among a vector of possible choices: $[0.1, 0.15, 0.5, 0.7, 0.95, 0.99, 1]$.
- Decision Tree. We use a 10-fold cross validation to choose the optimal minimal samples per leaf among a vector of possible choices: $[1, 5, 10, 20, 50, 100, 150, 500, 1000]$.
- Random Forest. We use a 10-fold cross validation to choose the optimal minimal samples per leaf among a vector of possible choices: $[5, 10, 20, 50, 100, 200, 500, 1000]$.
- XGBoost, by (6). We use a 10-fold cross validation to choose the optimal maximum number of leafs among a vector of possible choices: $[3, 5, 10, 20, 50, 100, 200, 500, 1000]$.
- K-Nearest Neighbors. We use a 10-fold cross validation to choose the optimal number of neighbors among a vector of possible choices: $[20, 50, 100, 200, 300, 500]$.

Overall, the voting ensemble is as good as every individual algorithms, and the accuracy is around 0.60.

Table S2. Model Performance Metrics, Citation Classification

Algorithm	F1 Score	Accuracy	N
Elastic Net	0.5621	0.5821	192,758
Regression Tree	0.5651	0.5764	192,758
Random Forest	0.5865	0.5974	192,758
XGBoost	0.5763	0.5868	192,758
K-Nearest Neighbors	0.5682	0.5884	192,758
Voting Ensemble	0.5797	0.5946	192,758

Polarization across Time

In our study, we re-examined the patterns presented in Figure 1 of the main paper, employing a linear regression model with fixed effects for Circuit Court and Legal Issue. This analysis aimed to assess polarization across three dimensions: prose, precedent, and policy. As shown in Figure S1, a marked increase in textual polarization is observed starting from the 1970s, indicating a shift towards more politically charged language in judicial opinions. In contrast, precedent polarization does not show a significant change, reinforcing the notion that language, rather than legal precedents, has become a primary medium for expressing politically motivated reasoning. Furthermore, dissent rates along party lines have been on the rise since the 1970s, suggesting an increasing tendency for judges to vote in accordance with their political affiliations.

Polarization by Topic

Our study further explores how the decrease in reasoning polarization, particularly under heightened scrutiny, varies across different legal topics. Utilizing the classification from the Songer database (7), we categorized cases into areas like criminal, civil rights, First Amendment, due process, labor relations, economic activity/regulation, privacy, and miscellaneous.

When examining judges on divided panels, we observed consistent polarization in text and citations across all legal topics. However, criminal and First Amendment cases displayed notably higher effects, as detailed in Tables S3 and S4. In terms of dissenting votes, judges showed a higher tendency to dissent in criminal and civil rights cases, while their behavior in First Amendment and economic cases remained relatively unchanged, as indicated in Table S5.

In the context of electoral cycles, we found a uniform decline in motivated reasoning in texts and citations for economic cases as midterm elections approached (Tables S6 and S7). This trend was less pronounced in other case types. Interestingly, judges demonstrated an increased rate of dissent in criminal, civil rights, labor relations, and economic cases during close presidential elections. Civil rights and economic cases also showed a significant uptick in dissent rates before midterm elections. Overall, these findings suggest that scrutiny's effect on motivated reasoning varies across legal topics, with ideologically contentious cases more susceptible to influence.

Polarization by Age and Experience

To explore the underlying mechanism of behavioral biases, we examined if such biases diminish with experience. Specifically, we focused on whether Type I biases, which may erode with experience, differ from Type II biases, like motivated reasoning, which are more reflective and intentional. Using the same linear regression framework, we analyzed how polarization in reasoning varies with judges' age and experience. Our findings, presented in Table S9 and S10, reveal that polarization in prose remains largely unchanged with age and experience, except for a notable decrease among very experienced judges. In contrast, precedent polarization shows a consistent decline with age and exhibits an inverted U-shaped pattern with experience. These results suggest that while judges' age and experience do not significantly impact polarization in their textual content, their selection of precedents becomes less polarized over time. This finding is particularly striking given the overall increase in textual polarization over the years, suggesting that this trend might not be primarily driven by the accumulation of judicial experience. Further research is necessary to fully understand these dynamics and the factors influencing them. These patterns, where prose polarization is mostly unaffected by experience and precedent polarization decreases with age, suggest that the biases observed lean towards Type II, being more reflective and intentional in nature.

Polarization in Vacancies

As noted by (8), since the era of President Eisenhower, there has been a growing trend for presidents to prefer individuals from federal courts as potential Supreme Court candidates. This preference may be attributed to the clearer ideological traceability of federal judges compared to candidates from other backgrounds. Since President Ford's nomination of Justice John G. Roberts, approximately 73% of the nominees have been Circuit Court judges. In light of this trend, our study focuses on all Supreme Court vacancies from 1975 to 2013. We consider the vacancy period, plus the six months preceding it, as our sample timeframe.

Following the approach of (9) for defining vacancies and contenders, we identify the start of a vacancy as the date a justice first informs the president of their intention to step down. The vacancy period ends when the Senate confirms the nomination. We define contenders as judges included in the president's shortlist for each vacancy, based on the criteria established by (8). Our analytical specification for examining the influence of promotion incentives on judicial polarization is outlined below:

$$Y_{it} = \alpha + \beta Vacancy_t + \gamma Contender_i + \delta Vacancy_t \times Contender_i + \boldsymbol{\eta'} \boldsymbol{Z}_{it} + \varepsilon_{it} \quad [1]$$

where Y_{it} is the polarization outcome (e.g. dissent rate), and $\boldsymbol{Z}_{it}$ are Circuit $\times$ Year and legal-issue fixed effects. We estimate the equation using OLS with robust standard errors clustered by individual judge. The coefficient of primary interest is δ, which measures the average difference in the polarization outcome, accounting for the fixed effects, for contenders during the periods of judicial vacancies.

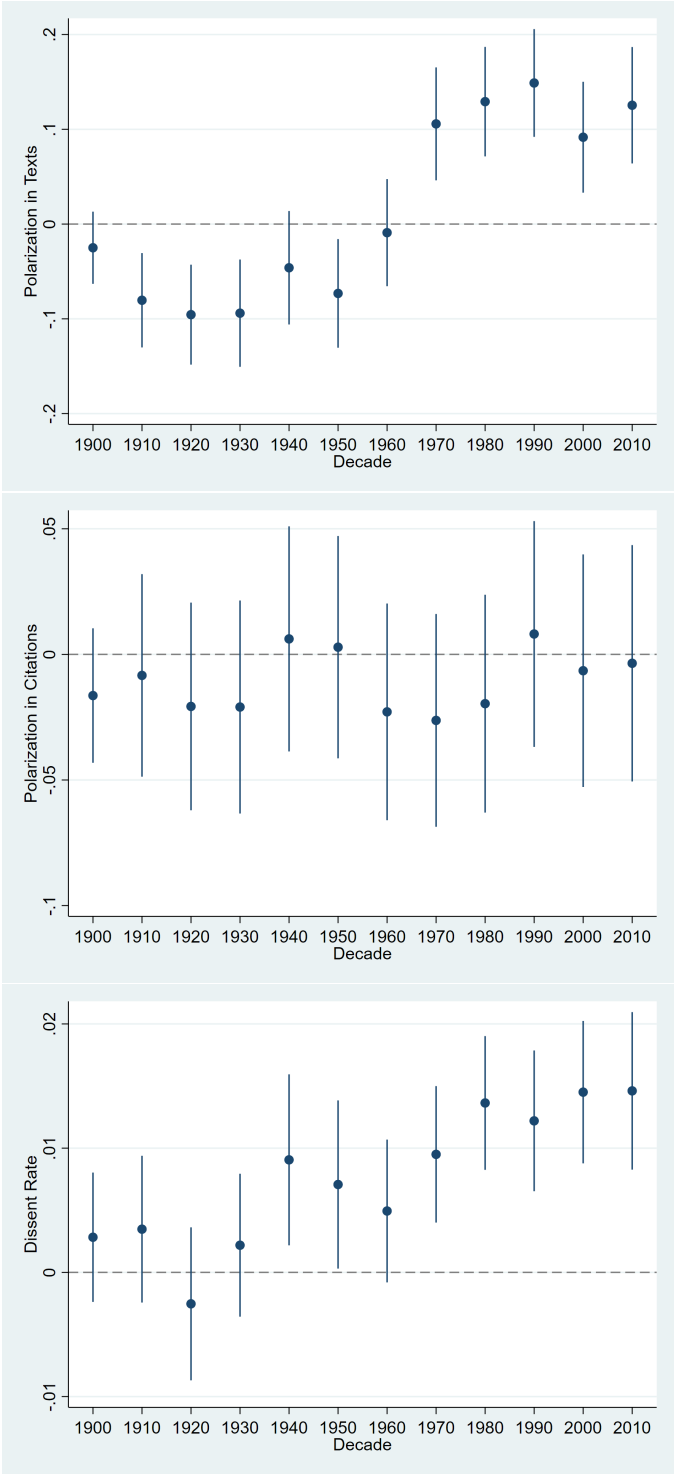

Fig. S1. Polarization in prose, Precedent, and Policy across time

Notes: The temporal changes in polarization in texts, citations, and dissent votes. The baseline level is 1890-1900. We control for Circuit and Legal Issue fixed effects. Standard errors clustered at judge level in parentheses.

Table S3. Polarization in Text by Topic

	(1) criminal	(2) civil rights	(3) First Amendment	(4) due process	(5) privacy	(6) labor relations	(7) economic activity and regulation	(8) miscellaneous
Divided	-0.044***	-0.032***	-0.052***	-0.033***	0.036	-0.025***	-0.024***	-0.028***
	(0.007)	(0.008)	(0.019)	(0.006)	(0.043)	(0.006)	(0.004)	(0.006)
Observations	67384	17838	1494	69095	164	15418	94649	43875
R^2	0.298	0.307	0.423	0.328	0.490	0.358	0.383	0.327
Circuit × Year FE	✓	✓	✓	✓	✓	✓	✓	✓

Notes: Standard errors clustered at judge level in parentheses. $*p < .1, **p < 0.05, ***p < .01$.

Table S4. Polarization in Citation by Topic

	(1) criminal	(2) civil rights	(3) First Amendment	(4) due process	(5) privacy	(6) labor relations	(7) economic activity and regulation	(8) miscellaneous
Divided	-0.050***	-0.042***	-0.043***	-0.040***	-0.025*	-0.034***	-0.028***	-0.032***
	(0.006)	(0.005)	(0.011)	(0.004)	(0.015)	(0.004)	(0.003)	(0.003)
Observations	62188	16140	1288	61493	147	13740	74250	39142
R^2	0.170	0.159	0.332	0.132	0.336	0.193	0.113	0.135
Circuit × Year FE	✓	✓	✓	✓	✓	✓	✓	✓

Notes: Standard errors clustered at judge level in parentheses. $*p < .1, **p < 0.05, ***p < .01$.

Table S5. Polarization in Votes by Topic

	(1) criminal	(2) civil rights	(3) First Amendment	(4) due process	(5) privacy	(6) labor relations	(7) economic activity and regulation	(8) miscellaneous
Divided	0.008***	0.011***	-0.012	0.005***	0.034	0.006***	0.001	0.010***
	(0.001)	(0.003)	(0.008)	(0.001)	(0.024)	(0.002)	(0.001)	(0.002)
Observations	234253	63234	4914	233658	877	51090	306412	135810
R^2	0.015	0.027	0.104	0.013	0.196	0.031	0.010	0.015
Circuit × Year FE	✓	✓	✓	✓	✓	✓	✓	✓

Notes: Standard errors clustered at judge level in parentheses. $*p < .1, **p < 0.05, ***p < .01$.

Table S6. Polarization in Text by Topic

	(1) criminal	(2) civil rights	(3) First Amendment	(4) due process	(5) privacy	(6) labor relations	(7) economic activity and regulation	(8) miscellaneous
Quarter to Elections=1	0.007	0.001	0.010	0.001	0.027	-0.011	0.010	0.002
	(0.008)	(0.014)	(0.050)	(0.008)	(0.210)	(0.015)	(0.008)	(0.009)
Quarter to Elections=2	0.015*	-0.017	-0.018	0.010	-0.088	-0.002	0.009	-0.009
	(0.008)	(0.013)	(0.047)	(0.007)	(0.138)	(0.016)	(0.008)	(0.009)
Quarter to Elections=3	0.022***	0.014	-0.031	0.005	0.060	0.004	0.012	-0.004
	(0.007)	(0.013)	(0.043)	(0.007)	(0.176)	(0.015)	(0.008)	(0.008)
Quarter to Elections=4	0.016**	0.011	-0.001	-0.000	0.306*	0.009	0.010	0.014
	(0.007)	(0.012)	(0.043)	(0.008)	(0.177)	(0.016)	(0.009)	(0.009)
Quarter to Elections=5	0.018*	0.022	0.083	-0.009	0.460	0.024	0.005	0.017
	(0.010)	(0.016)	(0.074)	(0.010)	(0.339)	(0.022)	(0.011)	(0.012)
Quarter to Elections=6	0.011	0.020	0.138*	-0.007	0.470	-0.003	0.004	-0.001
	(0.011)	(0.017)	(0.075)	(0.010)	(0.308)	(0.023)	(0.012)	(0.012)
Quarter to Elections=7	0.020*	-0.006	0.039	0.001	0.432	0.010	0.007	-0.006
	(0.011)	(0.017)	(0.070)	(0.011)	(0.261)	(0.024)	(0.012)	(0.012)
Quarter to Elections=8	-0.002	-0.010	0.070	-0.018**	0.613**	-0.020	-0.011	-0.004
	(0.010)	(0.015)	(0.078)	(0.009)	(0.253)	(0.021)	(0.010)	(0.010)
Quarter to Elections=9	-0.011	-0.011	0.061	-0.015	0.677**	-0.016	-0.028**	-0.004
	(0.011)	(0.019)	(0.087)	(0.011)	(0.272)	(0.025)	(0.012)	(0.013)
Quarter to Elections=10	-0.001	-0.004	0.069	-0.018	0.827***	-0.010	-0.021*	-0.029**
	(0.012)	(0.019)	(0.084)	(0.011)	(0.292)	(0.025)	(0.012)	(0.012)
Quarter to Elections=11	0.009	0.000	0.065	-0.015	0.732**	-0.004	-0.022*	-0.017
	(0.010)	(0.018)	(0.093)	(0.011)	(0.306)	(0.024)	(0.012)	(0.013)
Quarter to Elections=12	-0.001	-0.013	0.080	-0.023***	1.475***	-0.006	-0.012	-0.019**
	(0.008)	(0.013)	(0.073)	(0.008)	(0.452)	(0.018)	(0.009)	(0.009)
Quarter to Elections=13	0.016*	-0.015	0.105	-0.020**	1.405***	0.012	0.006	-0.023**
	(0.009)	(0.015)	(0.091)	(0.009)	(0.417)	(0.018)	(0.011)	(0.010)
Quarter to Elections=14	0.011	-0.025	0.174*	-0.013	1.473***	-0.009	-0.015	-0.026***
	(0.010)	(0.015)	(0.103)	(0.009)	(0.446)	(0.019)	(0.010)	(0.009)
Quarter to Elections=15	0.022**	-0.018	0.076	-0.009	1.472***	-0.007	-0.003	-0.021**
	(0.009)	(0.014)	(0.093)	(0.008)	(0.433)	(0.018)	(0.009)	(0.009)
Observations	48297	14383	1220	48813	153	9309	34730	33026
R^2	0.224	0.259	0.381	0.257	0.576	0.290	0.274	0.264
Circuit × Year FE	✓	✓	✓	✓	✓	✓	✓	✓

Notes: Standard errors clustered at judge level in parentheses. $*p < .1, **p < 0.05, ***p < .01$.

Table S7. Polarization in Citation by Topic

	(1) criminal	(2) civil rights	(3) First Amendment	(4) due process	(5) privacy	(6) labor relations	(7) economic activity and regulation	(8) miscellaneous
Quarter to Elections=1	-0.005	0.000	-0.021	0.002	0.004	-0.012*	-0.004	0.001
	(0.004)	(0.006)	(0.017)	(0.005)	(0.035)	(0.007)	(0.004)	(0.004)
Quarter to Elections=2	0.005	-0.004	0.002	0.006	0.022	0.003	-0.001	0.001
	(0.004)	(0.006)	(0.019)	(0.004)	(0.050)	(0.008)	(0.004)	(0.003)
Quarter to Elections=3	0.002	0.003	0.012	0.009***	0.089**	-0.001	-0.002	0.005*
	(0.004)	(0.005)	(0.018)	(0.003)	(0.035)	(0.007)	(0.004)	(0.003)
Quarter to Elections=4	-0.001	-0.003	0.004	0.004	0.067	0.006	-0.004	0.004
	(0.004)	(0.005)	(0.021)	(0.003)	(0.076)	(0.008)	(0.004)	(0.003)
Quarter to Elections=5	-0.000	-0.001	-0.005	-0.000	0.086	0.008	-0.009*	0.001
	(0.005)	(0.008)	(0.029)	(0.005)	(0.082)	(0.010)	(0.005)	(0.005)
Quarter to Elections=6	-0.003	0.005	0.015	0.000	0.105	0.008	-0.005	0.004
	(0.006)	(0.008)	(0.028)	(0.005)	(0.085)	(0.010)	(0.005)	(0.005)
Quarter to Elections=7	-0.003	-0.005	0.005	0.002	0.080	0.013	-0.007	0.001
	(0.005)	(0.007)	(0.026)	(0.005)	(0.069)	(0.010)	(0.005)	(0.005)
Quarter to Elections=8	-0.004	-0.007	-0.017	0.002	0.033	0.005	-0.008*	0.003
	(0.005)	(0.007)	(0.028)	(0.004)	(0.113)	(0.009)	(0.005)	(0.004)
Quarter to Elections=9	-0.000	-0.012	0.009	0.004	0.103	0.008	-0.016***	0.001
	(0.006)	(0.009)	(0.029)	(0.005)	(0.110)	(0.011)	(0.006)	(0.005)
Quarter to Elections=10	0.005	-0.010	0.028	-0.000	0.092	0.006	-0.011**	0.000
	(0.006)	(0.008)	(0.029)	(0.005)	(0.113)	(0.011)	(0.005)	(0.005)
Quarter to Elections=11	0.004	-0.005	0.009	-0.001	0.123	0.007	-0.009	0.006
	(0.006)	(0.007)	(0.028)	(0.005)	(0.131)	(0.011)	(0.006)	(0.005)
Quarter to Elections=12	0.001	-0.004	0.008	-0.003	0.064	0.006	-0.008**	-0.004
	(0.004)	(0.006)	(0.025)	(0.004)	(0.128)	(0.009)	(0.004)	(0.004)
Quarter to Elections=13	0.007	0.001	0.003	-0.006	0.077	0.012	-0.000	-0.005
	(0.004)	(0.006)	(0.025)	(0.005)	(0.165)	(0.009)	(0.005)	(0.004)
Quarter to Elections=14	0.007	-0.003	-0.001	-0.003	0.059	0.017*	-0.007	-0.005
	(0.005)	(0.007)	(0.026)	(0.004)	(0.115)	(0.009)	(0.005)	(0.004)
Quarter to Elections=15	0.008*	-0.007	0.021	-0.002	0.180	0.020**	-0.004	-0.001
	(0.005)	(0.006)	(0.024)	(0.004)	(0.117)	(0.008)	(0.004)	(0.004)
Observations	46161	13384	1087	45986	143	8758	31974	30893
R^2	0.131	0.111	0.311	0.099	0.435	0.128	0.089	0.088
Circuit × Year FE	✓	✓	✓	✓	✓	✓	✓	✓

Notes: Standard errors clustered at judge level in parentheses. $*p < .1, **p < 0.05, ***p < .01$.

Table S8. Polarization in Votes by Topic

	(1) criminal	(2) civil rights	(3) First Amendment	(4) due process	(5) privacy	(6) labor relations	(7) economic activity and regulation	(8) miscellaneous
Quarter to Elections=1	0.007**	0.018***	0.020	-0.005	-0.025	0.018**	0.007**	0.002
	(0.003)	(0.007)	(0.028)	(0.003)	(0.056)	(0.008)	(0.003)	(0.005)
Quarter to Elections=2	0.002	0.016**	0.008	-0.001	0.039	0.012	0.004	0.003
	(0.003)	(0.006)	(0.027)	(0.003)	(0.058)	(0.008)	(0.004)	(0.004)
Quarter to Elections=3	0.003	0.009	0.023	0.000	0.022	0.013	0.002	0.002
	(0.003)	(0.006)	(0.034)	(0.003)	(0.073)	(0.008)	(0.003)	(0.004)
Quarter to Elections=4	-0.000	0.009	0.021	-0.002	0.070	0.006	-0.005	-0.004
	(0.003)	(0.007)	(0.035)	(0.003)	(0.074)	(0.008)	(0.004)	(0.005)
Quarter to Elections=5	0.001	0.015*	0.004	-0.005	0.063	0.006	0.005	0.002
	(0.004)	(0.009)	(0.045)	(0.004)	(0.086)	(0.010)	(0.005)	(0.006)
Quarter to Elections=6	-0.003	0.012	0.007	-0.001	0.109	0.002	0.004	0.000
	(0.004)	(0.009)	(0.044)	(0.004)	(0.105)	(0.011)	(0.005)	(0.006)
Quarter to Elections=7	-0.001	0.006	-0.010	-0.000	0.070	0.003	-0.003	-0.003
	(0.004)	(0.008)	(0.045)	(0.004)	(0.074)	(0.011)	(0.005)	(0.006)
Quarter to Elections=8	0.000	0.010	-0.002	-0.000	0.092	0.004	0.004	-0.004
	(0.004)	(0.008)	(0.044)	(0.004)	(0.074)	(0.010)	(0.004)	(0.005)
Quarter to Elections=9	0.005	0.016*	-0.027	-0.003	0.066	0.003	0.008*	0.007
	(0.004)	(0.009)	(0.049)	(0.004)	(0.090)	(0.012)	(0.005)	(0.006)
Quarter to Elections=10	0.005	0.012	-0.034	-0.002	0.088	0.002	0.008	-0.001
	(0.004)	(0.009)	(0.048)	(0.005)	(0.093)	(0.012)	(0.005)	(0.006)
Quarter to Elections=11	0.006	0.003	-0.034	0.002	0.149*	0.000	0.004	-0.001
	(0.004)	(0.009)	(0.052)	(0.004)	(0.083)	(0.011)	(0.005)	(0.006)
Quarter to Elections=12	-0.002	0.008	-0.002	-0.001	-0.017	0.003	0.001	-0.009*
	(0.003)	(0.007)	(0.038)	(0.003)	(0.050)	(0.008)	(0.004)	(0.005)
Quarter to Elections=13	0.004	0.008	0.003	-0.005	-0.036	-0.004	0.006	-0.005
	(0.003)	(0.007)	(0.037)	(0.004)	(0.070)	(0.009)	(0.004)	(0.005)
Quarter to Elections=14	-0.002	0.003	-0.022	-0.007**	-0.013	-0.007	0.005	-0.002
	(0.004)	(0.007)	(0.037)	(0.003)	(0.068)	(0.009)	(0.004)	(0.005)
Quarter to Elections=15	0.001	0.007	0.022	-0.004	-0.004	-0.009	0.003	-0.010*
	(0.003)	(0.007)	(0.041)	(0.003)	(0.067)	(0.008)	(0.004)	(0.005)
Observations	156582	45754	3787	158722	806	29627	111683	99964
R^2	0.011	0.020	0.106	0.010	0.186	0.022	0.010	0.011
Circuit × Year FE	✓	✓	✓	✓	✓	✓	✓	✓

Notes: Standard errors clustered at judge level in parentheses. $*p < .1, **p < 0.05, ***p < .01$.

Table S9. The effect of age on polarization

	(1) Text	(2) Citation
Experience	-0.001	0.000
	(0.001)	(0.001)
Age $\in [40, 45)$	-0.026	-0.030***
	(0.042)	(0.010)
Age $\in [45, 50)$	-0.027	-0.049***
	(0.049)	(0.011)
Age $\in [50, 55)$	-0.016	-0.059***
	(0.049)	(0.011)
Age $\in [55, 60)$	-0.016	-0.057***
	(0.049)	(0.012)
Age $\in [60, 65)$	-0.023	-0.063***
	(0.050)	(0.013)
Age $\in [65, 70)$	-0.020	-0.069***
	(0.051)	(0.015)
Age $\in [70, 75)$	-0.020	-0.078***
	(0.053)	(0.017)
Age $\in [75, 80)$	-0.023	-0.084***
	(0.056)	(0.020)
Age $\in [80, 85)$	-0.023	-0.095***
	(0.061)	(0.023)
Age $\in [85, 90)$	-0.040	-0.126***
	(0.068)	(0.027)
Age $\in [90, 95)$	-0.035	-0.115***
	(0.082)	(0.043)
Age $\in [95, 100)$	0.014	-0.062
	(0.100)	(0.044)
Observations	312928	271057
R^2	0.334	0.113
Circuit $\times$ Year FE	✓	✓
Legal Issue FE	✓	✓

Notes: The baseline level is Age $\in [35, 40)$. Standard errors clustered at judge level in parentheses. $*p < .1, **p < 0.05, ***p < .01$.

Table S10. The effect of experience on polarization

	(1) Text	(2) Citation
Age	-0.000	-0.001***
	(0.001)	(0.001)
Experience $\in [5, 10)$	-0.000	0.004
	(0.005)	(0.003)
Experience $\in [10, 15)$	-0.008	-0.001
	(0.010)	(0.006)
Experience $\in [15, 20)$	-0.002	0.017*
	(0.016)	(0.009)
Experience $\in [20, 25)$	-0.005	0.025*
	(0.021)	(0.013)
Experience $\in [25, 30)$	-0.025	0.010
	(0.027)	(0.017)
Experience $\in [30, 35)$	-0.030	-0.007
	(0.033)	(0.022)
Experience $\in [35, 40)$	-0.034	-0.006
	(0.041)	(0.033)
Experience $\in [40, 45)$	-0.032	-0.052
	(0.054)	(0.036)
Experience $\in [45, 50)$	-0.176***	-0.105***
	(0.053)	(0.034)
Experience $\in [50, 55)$	-0.382***	-0.051
	(0.062)	(0.033)
Observations	312928	271057
R^2	0.335	0.117
Circuit $\times$ Year FE	✓	✓
Legal Issue FE	✓	✓

Notes: The baseline level is Experience $\in [0, 5)$ years. Standard errors clustered at judge level in parentheses. $*p < .1, **p < 0.05, ***p < .01$.

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