

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

Wei Lu\*

Daniel L. Chen<sup>†</sup>

October 28th, 2024

## Abstract

This study explores politically motivated reasoning among U.S. Circuit Court judges over the past 120 years, examining their writing style and use of previous case citations in judicial opinions. Employing natural language processing and supervised machine learning, we scrutinize how judges' language choices and legal citations reflect partisan slant. Our findings reveal a consistent, albeit modest, polarization in citation practices. More notably, there is a significant increase in polarization within the textual content of opinions, indicating a stronger presence of motivated reasoning in their prose. We also examine the impact of heightened scrutiny on judicial reasoning. On divided panels and as midterm elections draw near, judges show an increase in dissent votes while decreasing in polarization in both writing and citation practices. Furthermore, our study explores polarization dynamics among judges who are potential candidates for Supreme Court promotion. We observe that judges on the shortlist for Supreme Court vacancies demonstrate greater polarization in their selection of precedents.

---

\*Zicklin School of Business, CUNY-Baruch College. Email: [wei.lu@baruch.cuny.edu](mailto:wei.lu@baruch.cuny.edu)

<sup>†</sup>Toulouse School of Economics, Institute for Advanced Study in Toulouse, University of Toulouse Capitole. Email: [daniel.chen@iast.fr](mailto:daniel.chen@iast.fr). Work on this project was conducted while Daniel Chen received financial support from the European Research Council (Grant No. 614708), Swiss National Science Foundation (Grant Nos. 100018-152678 and 106014-150820), and Agence Nationale de la Recherche. Latest version at: [http://nber.org/~dlchen/papers/Motivated\\_Reasoning\\_in\\_the\\_Field.pdf](http://nber.org/~dlchen/papers/Motivated_Reasoning_in_the_Field.pdf).

“I pay very little attention to legal rules, statutes, constitutional provisions ... The first thing you do is ask yourself — forget about the law — what is a sensible resolution of this dispute? ... See if a recent Supreme Court precedent or some other legal obstacle stood in the way of ruling in favor of that sensible resolution. ... When you have a Supreme Court case or something similar, they’re often extremely easy to get around.” (*An Exit Interview with Richard Posner*, The New York Times, Sep. 11, 2017).

## 1 Introduction

Can we quantitatively identify when judges have an easier time recruiting evidence supporting what they want to be true than evidence supporting what they want to be false [Epley and Gilovich \(2016\)](#)? This tendency is called motivated reasoning, and several recent models and experiments on motivated reasoning are summarized in [Bénabou and Tirole \(2016\)](#). Motivated reasoning is a subject of much policy debate. Does it affect real-world decision-makers? Moreover, what affects motivated reasoning? These are the core questions this paper seeks to address. Motivated reasoning is the well-documented tendency of individuals to actively seek out confirmatory information. The mechanism is said to be implicit emotion regulation, where the brain converges on judgments that maximize positive affective states associated with the attainment of motives. In controlled settings, motivation is typically inferred by the degree to which goal-related concepts are accessible in memory: the greater the motivation, the more likely individuals are to remember, notice, or recognize concepts, objects, or persons related to that goal [Touré-Tillery and Fishbach \(2014\)](#).<sup>1</sup> Recently, motivated reasoning has been used to explain polarization. For example, when responding to moral dilemmas, subjects come to snap judgments and then generate a post hoc justification [Haidt \(2000\)](#); similarly, when interpreting data on climate change, subjects update their beliefs along party lines, particularly among those with higher cognitive reflection [Kahan \(2013\)](#).

---

<sup>1</sup>The classic studies measure the final decision rather than reasoning [Zeigarnik \(1927\)](#); [Förster et al. \(2005\)](#).

In prior studies of motivating reasoning in law, law student subjects are exogenously provided precedents (reasons) [Braman \(2006\)](#); [Braman and Nelson \(2007\)](#)) to address the issue that differences in reasoning might be due to memory or knowledge. The experiments fix the set of precedents to choose from. Nevertheless, whether these studies on law students are externally valid to judges or other policymakers is still an open question [Sood \(2013\)](#). In another study using a series of experiments on statutory interpretation with the cultural identity of parties involved as the main manipulation, [Kahan et al. \(2015\)](#) shows that judges and lawyers do not exhibit cultural biases, unlike law students and the general public. In our case, we show that when judges are making high-stakes decisions in Court, they could exhibit polarization in writing. Building on the framework by [Kahan \(2016\)](#) on politically motivated reasoning, recent work by [Thaler \(2020\)](#) provides a new design to assess politically motivated reasoning based on trust in news.

This paper explores motivated reasoning among real-world judges. Our paper sits at the intersection of constitutional law, politics, and judicial legitimacy, examining the hypothesis that judicial decision-making is politically motivated. Grounded in the debate between jurisprudential decisionism and the separation of political interests from legal procedures [Schmitt \(1969, 1985, 2005\)](#); [Berger \(1997\)](#); [Hirschl \(2009\)](#); [Levinson \(2006\)](#); [Doerfler and Moyn \(2020\)](#), we employ a quantitative approach to assess the extent to which recent shifts in the U.S. judiciary reflect broader political dynamics. Our analysis contributes to the understanding of how constitutional-legal proceduralism, often seen as a tool for upholding democratic values, may be exploited by political-economic elites to shape legal outcomes. This paper provides empirical insights into the political nature of judicial decision-making, offering a novel perspective in the context of ongoing debates on the judiciary's role in liberal democracies.

Specifically, we aim to analyze motivated reasoning using as a natural laboratory the U.S. federal courts – a high-stakes common-law space. Circuit Court judges are appointed by the U.S. president (Democrat or Republican) with life tenure. Circuit judges can introduce new legal theo-

ries,<sup>2</sup> shift standards or thresholds,<sup>3</sup> and rule on the constitutionality of federal and state statutes. Circuit judges provide the final decision on tens of thousands of cases per year, compared to just a hundred cases or so on the U.S. Supreme Court. Therefore Circuit decisions are the majority of what creates the law in this common-law space (and most of what law students are reading). If there is motivated reasoning among these judges, that could have substantial legal and policy impacts. Existing research on how Democrat and Republican Circuit Court judges behave differently is extensive (see [Bonica and Sen \(2021\)](#) for a comprehensive review), but almost all of them focus on the decisions made by judges. For example, a recent work examines how the ideology of Circuit Court judges can affect case outcomes in a wide range of Circuit cases [Cohen \(2023\)](#). Our paper complements this literature by shifting attention to polarization in reasoning.

Circuit courts have a handful of critical features that make them a desirable context for this empirical work. First, there is random assignment of cases to judges (who sit in panels, without juries),<sup>4</sup> meaning that judges rule on similar legal issues on average. Second, there is an adversarial system where the litigants are responsible for bringing all the reasons (arguments and precedents) to a judge's attention. This means that differences in reasoning are not due to differences in knowledge.<sup>5</sup> In addition, the briefs are filed prior to judicial assignment, so strategic information provision according to judge type is not feasible.

Motivated reasoning can be understood as a cognitive process where individuals distort how they interpret information to align with their pre-existing beliefs, often to reduce cognitive dissonance. [Thaler \(2020\)](#)'s framework on politically motivated reasoning provides a clear explanation of how and why this occurs, especially in politically charged contexts. His experimental work

---

<sup>2</sup>E.g., contract duty posits a general obligation to keep promises, vs. a party should be allowed to breach a contract and pay damages if it's more economically efficient than performing, also known as efficient breach theory, articulated by Richard Posner in a 1985 opinion.

<sup>3</sup>(E.g., shift from reasonable person standard to reasonable woman standard for what constitutes sexual harassment, or waive the need to prove emotional harm in court to a jury.)

<sup>4</sup>This randomness has been used in a growing set of economics papers [Kling \(2006\)](#); [David et al. \(2015\)](#); [Belloni et al. \(2012\)](#); [Dahl et al. \(2014\)](#); [Mueller-Smith \(2015\)](#); [Beim et al. \(2021\)](#).

<sup>5</sup>That is, we can distinguish our results from mechanical failures of inference due to bounded rationality or limited attention; in this adversarial setting, briefs bring forward all the citable reasons.

shows that individuals do not update their beliefs in a purely Bayesian manner when receiving new information. Instead, they give greater weight to information that reinforces their prior beliefs and are more skeptical of information that challenges those beliefs. Applied to judges, this framework helps explain why judicial reasoning can exhibit ideological polarization. Even though judges are expected to be impartial, their political affiliation and identity can lead them to unconsciously distort how they interpret legal precedents or facts, much like how Thaler's subjects over-trusted news that supported their political stances. In legal contexts, where ambiguity often exists, this motivated reasoning can manifest as judges unconsciously favoring interpretations of the law that align with their political preferences. Thaler's model also predicts that the stronger an individual's prior beliefs (such as a judge's political affiliation), the more likely they are to exhibit overconfidence in the correctness of their reasoning, further reinforcing polarized judicial opinions.

We analyze over 300,000 Circuit Court opinions (representing almost a million judicial votes) from 1891 to 2013, assessing judicial reasoning through both the text of the opinions and citations to other Circuit Court rulings. These outcomes are linked to judicial biographical factors, particularly political affiliation. In this study, polarization is defined as the degree to which judicial opinions and citation patterns reflect partisan divides, with the reasoning aligning with the judge's political party. We argue that this polarization is an observable result of politically motivated reasoning, where judicial reasoning demonstrates ideological biases consistent with the judge's political preferences. Motivated reasoning often skews the decision-making process towards political beliefs, as noted by [Thaler \(2020\)](#), leading judges to unconsciously favor legal interpretations that support their ideological views. This bias results in judges giving more weight to evidence or precedents that align with their pre-existing political beliefs, reinforcing partisan divisions in their legal reasoning. Thus, polarization in judicial opinions can be seen as a direct consequence of motivated reasoning, where cognitive biases lead judges to unconsciously align their reasoning with their political preferences.

The degree of polarization is measured by the accuracy with which we can predict a judge's

political affiliation based on the content and structure of their opinions, following the approach of previous studies [Gentzkow et al. \(2019\)](#); [Bertrand et al. \(2018\)](#). Earlier efforts to measure polarization in the text, such as [Jensen et al. \(2012\)](#), might overestimate polarization in early years. Our approach improves upon this by focusing specifically on judicial texts, where political bias can be observed in both language and citation practices. Outside the legal context, [Jelveh et al. \(2018\)](#) use the text of academic articles to predict political donations by economists. Unlike economists or members of Congress, who have discretion over the topics they address, judges are randomly assigned cases. This ex-ante assignment makes judicial reasoning a more direct reflection of political bias. Moreover, political donations are made after (ex-post) economist writings, while the political affiliation of the appointing party is determined before (ex-ante) judicial writings. We seek to predict a predetermined measure of ideology prior to reasoning on the case.

Compared to the extant literature on political polarization, the contribution of our paper is twofold. Firstly, we study how polarization is manifested in both judicial reasoning and policy decisions. While research on the latter is abundant [Hasen \(2019\)](#), little is known about how the reasoning process of judges can inform their political preferences. By examining the language and citation patterns in judicial opinions, we provide new insights into how judges’ political affiliations may influence their legal reasoning, complementing the existing literature that primarily focuses on judicial votes and outcomes.

Secondly, we leverage recent advances in machine learning and natural language processing to measure motivated reasoning using a very large dataset of citations and texts. Compared to previous studies that rely on votes or appointment variables, the adoption of these methods allows us to make use of the high-dimensional dataset on judicial behavior to answer our question of interest. This approach is particularly valuable given the complex nature of legal texts [Bonica and Sen \(2021\)](#), as it enables us to uncover nuanced patterns of polarization that may not be readily apparent using traditional methods.

In less technical terms, we “train” the machine-learning model on a large set of texts where

we already know the judges political affiliation. The model then learns which linguistic features (words, phrases, types of arguments, etc.) are more frequently used by judges from each political party. Once trained, the model can take a new judicial opinion, analyze its language, and estimate how likely the judge is to align with a particular political ideology based on the patterns in their writing.

This measure of polarization reflects how much the language in an opinion resembles the typical language used by judges of a specific political party. If the opinion strongly mirrors the patterns associated with one party, we interpret this as evidence of politically motivated reasoning. Conversely, if the opinion uses language that doesn't clearly align with any political party, it would suggest a lower degree of polarization.

A new contribution is to look at the polarization of precedent, as these are the legal reasons cited to justify a decision. We use a network of citations to previous Circuit Court decisions to predict partisan affiliation. Unlike the case of prose, we find low yet steady levels of precedent polarization over time, indicating that judges tend to express ideological differences through writing instead of choices of precedents in our context. These results complement previous work with smaller samples by [Choi and Gulati \(2008\)](#) showing that circuit judges tend to cite judges from the same party, and that of [Niblett and Yoon \(2016\)](#) showing that circuit judges tend to cite Supreme Court cases authored by judges from the same party.

Finally, we look at how the polarization in prose and precedent changes when judges are under more scrutiny. Specifically, we examine two such scenarios: The first is whether a judge sits on a divided panel of judges from both parties. The second scenario is whether the opinions were filed when the midterm or presidential elections were close. Some research suggests that the threat of actual “whistleblowing” tempers the decisions issued when under scrutiny [Cross and Tiller \(1997\)](#); [Berdejó and Chen \(2017\)](#), as reflected by the increase in dissents. Consistent with this interpretation, the polarization in text and citations reduces when under scrutiny. Moreover, we examine how polarization varies when judges have promotion incentives. We find that judges

exhibit more polarization in precedent when they are a contender for a Supreme Court vacancy.

## 2 Measuring motivated reasoning in judicial context

In this paper, we define “motivated reasoning” in the judicial context as the ability to predict a judge’s political affiliations based on the way they write opinions and cite precedents. Existing literature in economics has shown that the predictability/the prediction accuracy of texts and other behaviors can be used as valid measures of party differences and cultural distance [Gentzkow et al. \(2019\)](#); [Bertrand et al. \(2018\)](#). Intuitively, if we can infer a judge’s political affiliation from his or her reasoning process, it is probable that political considerations is playing a role in such process, especially in precedents where judges have the discretion to select the relevant cases.

[Kahan \(2016\)](#) provides a theoretical framework for this measure. They propose that politically motivated reasoning in our setting can be defined as the distortion of how political dispositions (political party) affect the way a judge interprets new evidence (cases) to update his prior beliefs to form a posterior (reflected by texts and citations in opinions). Three features of the institutional setting ensure that the predictability measure we have is not related to varying priors or new evidence, and the predictability of political parties can be attributed to the distortion caused by political dispositions.

Firstly, the style and content of a judge’s opinions, along with their chosen citations, offer insights into their formal reasoning processes. Prior literature has shown that judicial fact discretion, how judges believe and interpret the facts presented, can be related to the identity of judges [Gennaioli and Shleifer \(2008\)](#). Since how judges recruit precedents and prose in their opinions constitutes the judicial opinion, we would be observing any slant in the formal reasoning process made explicit in their opinion.

Secondly, the cases are assigned quasi-randomly to judges <sup>6</sup>. The as-if random assignment

---

<sup>6</sup>Some research suggests that a few of the courts do not assign cases to judges completely randomly, but the reasons for non-random assignment include workload, scheduling, and professional development [Levy \(2017\)](#). There



of cases means that every judge will on average see a similar variety of cases. Notably, cases that should cite certain precedents or refer to certain topics should not systematically differ across judges due to this random assignment process.

Thirdly, absent politically motivated reasoning, the reasoning in the cases should be non-partisan because judges are asked that they “*not be swayed by partisan interests*”<sup>7</sup>. If judges follow this edict, then a reasonable guess on party affiliation based on the opinion is 0.5 – i.e., the probabilities of the writer being a member of Republican Party or a Democratic Party should be the same. However, this might diverge if judges are systematically interpreting the facts and the law in a different manner that is reflective of their political party.

If the expressed reasoning of judges is motivated by partisan views, then the choice of language and citations might be informative of the political party. Motivated reasoning can alter the way judges interpret and evaluate information from briefs and precedents, which would lead to differences in their expressed arguments. If a judge’s political affiliations can be predicted based on their writing and citations to legal precedent, it would suggest that their reasoning can be influenced by their political leanings.

## 2.1 Data

Our dataset includes a collection of 318,474 opinions published by U.S. Circuit Courts from 1891 to 2013 based on [Berdejó and Chen \(2017\)](#). We limit our analysis to opinions written by one judge, excluding opinions labeled *per curiam*, which are authored by the whole panel without designating a specific author, and opinions drafted by multiple judges. Among all opinions, 279,167 are majority opinions and 26,441 are dissent opinions. For each opinion, we observe the full text, legal precedents, as well as all votes cast by judges on the panels for each case. We focus on precedents of previous Circuit Court opinions and the partisan policy is constructed using data on judge dissenting votes.

---

is no direct evidence that political party is related to the assignment of cases.

<sup>7</sup><http://www.uscourts.gov/judges-judgeships/code-conduct-united-states-judges>

To study the heterogeneity of motivated reasoning across judicial characteristics, we link the opinions to the United States Courts of Appeals Databases and Attributes of the United States Federal Court Judges from [Songer \(Last visited June 20, 2018\)](#), and use variables such as political affiliations of judges, Circuit Court, the political composition of panels, year, quarter to presidential elections for subsequent analysis.

## 2.2 Classification

Since the predictability of judicial reasoning serves as our measure of motivated reasoning, we conceptualize this measurement problem as equivalent to a binary classification problem in machine learning using high-dimensional text and citation data as inputs and the political affiliations of judges as the outcome variable. In our two prediction tasks, we aim to predict the political affiliation of circuit court judges, specifically whether they belong to the Democratic or Republican party. The affiliation is represented by a binary variable: “1” for Democratic judges and “0” for Republican judges. We use opinion texts and citation embeddings as our predictors. To determine a judge’s average stance over a year, we average these embeddings. Our goal is to predict the likelihood that a judge’s political affiliation matches their true party affiliation.

We use sample splitting to avoid overfitting the models. In Text Classification, we randomly chose 10% of our dataset, which is about 31,000 opinions as our sample dataset due to computational constraints. Afterward, 30% of the 10% sample is used as the test set and the remaining 70% as the training set. For Citation Classification, we use the full dataset as our sample dataset, with 30% as the test set. The test set is only used after training to assess the performance of the algorithms. The best model (an ensemble of models with best-performing parameters) in each task will be applied to the full sample to generate predictions for all opinions. The remaining strategies and training details are in the SI Appendix.

## 2.3 Training Algorithms for Texts

Using texts for predictions is not a trivial task, especially given the amount of words and documents in our sample. We leverage recent advances in natural language processing to classify political affiliations of Circuit Court judges by fine-tuning pre-trained large language models using opinion texts directly as inputs. In recent years, transformer-based pre-trained large language models have been proven to have satisfactory performance on a variety of NLP tasks. Even with a small sample for fine-tuning, pre-trained models can further significantly improve the performance [Devlin et al. \(2018\)](#). In this paper, we will use an ensemble of several commonly-used pre-trained transformer models to ensure the robustness of our results by averaging the predictions across models. Before fine-tuning, for each opinion, we use the Microsoft Presidio tool [Mendels et al. \(2018\)](#) to detect and replace all names (including judges and any person’s names) and locations to the word “PERSON” and “LOCATION”. Doing so will prevent the pre-trained models from relying on the name and location information for classification, a problem known as data leakage. After that, the first 512 words of each opinion, which is the maximum length allowed by models, will be used as inputs for pre-trained models to learn.

## 2.4 Training Algorithms for Citations

For precedents, we combine network representation models with ensemble supervised learning for classification. In the first step, we construct and transform the citation network into dense low-dimensional vectors. Specifically, we create a weighted directed graph of 310,282 nodes, and transform the citation network into citation embeddings of 300 dimensions using the node2vec algorithm by [Grover and Leskovec \(2016\)](#). The node2vec algorithm rests on the idea that a word is represented by its “neighboring words” [Firth \(1957\)](#) in natural language processing. It adopts a random walk approach across the network to generate sequences of citations, and by maximizing the probability of neighboring citations, we can have latent vectors that “*maximize the likelihood of preserving network neighborhoods*” of citations. Then, we use an ensemble of commonly used

supervised machine learning algorithms as our prediction algorithm, consistent with similar strategies used in previous literature [Bertrand and Kamenica \(2018\)](#).

## 2.5 Permutation Inference

To ensure that the algorithms are indeed learning from the training set, we generate a random permutation of political parties with an equal probability of two parties for all authors and use this list as the dependent variable for training. If the algorithms are learning correctly from the data, using random series as the dependent variable should result in random predictions. A similar strategy is also implemented by [Gentzkow et al. \(2019\)](#), who randomly shuffle the share of Republicans/Democrats in Congress during the year in which a particular congressman. In practice, we train another set of models with the same parameters on the random series for both Text and Citation Classification.

# 3 Results

## 3.1 Polarization in Prose and Precedents across time

We begin with an overview of how polarization in prose and precedent evolves over time. Figure 1 illustrates the trend in average polarization levels within opinion texts. The magnitude of average polarization in writing consistently exceeds 0.5 and surged towards 0.8 after 1950. These trends imply an increasing propensity for motivated reasoning among judges when drafting their opinions. Although [Gentzkow et al. \(2019\)](#) identified an increase in polarization in congressional speeches after 2000, it is significantly lower compared to the polarization observed in judicial opinions. To put this effect size in perspective, in [Gentzkow et al. \(2019\)](#), the polarization varies between 0.5 and 0.515. Notably, the placebo test involving random shuffling series aligns closely with the 0.5 benchmark, validating our models' ability to produce random predictions when analyzing data with randomly permuted party affiliations of judges. The fact that polarization was more present a century ago is consistent with other analyses of partisan behavior in the judiciary

Chen (2024). In the analyses that follow, we demonstrate how scrutiny influences this measure of partisanship, taking into account the specific time period in question.

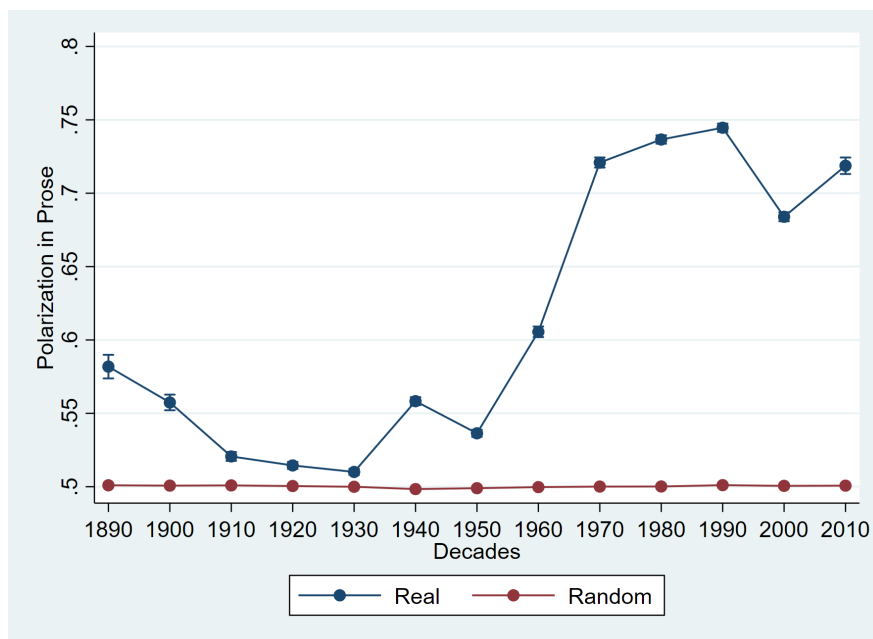


Figure 1: Polarization in Prose in U.S. Circuit Courts

*Notes:* Polarization measures over time in U.S. Circuit Courts, 1891-2013 for writing. The blue line gives the average polarization in the true dataset. The red line gives the average polarization in the shuffled dataset (random party affiliations). Error bars indicate the 99% confidence interval.

Furthermore, we investigate the presence of motivated reasoning in the selection of precedents by judges. Figure 2 shows that, over the past 120 years, Circuit Court judges have consistently demonstrated a lower level of motivated reasoning in their choice of legal precedents, especially when compared to the more pronounced motivated reasoning observed in texts. This suggests that, unlike the choice of language, judges are more constrained in their choice of precedents. However, the level of polarization is still distinguishable from the placebo random series of 0.5 and higher than the polarization in congressional speech found in Gentzkow et al. (2019).

The higher levels of polarization in prose compared to precedents indicate that judges may have more discretion in how they frame and articulate their arguments than in their selection of legal authorities. One potential explanation might be the rhetorical style of judicial overstating,

a product of cognitive processes and a means to enhance the judiciary’s legitimacy [Simon and Scurich \(2014\)](#). On the other hand, Circuit Court judges may be constrained by precedents as they face the reversal from higher courts if deviating too much from precedent [Hasen \(2019\)](#).

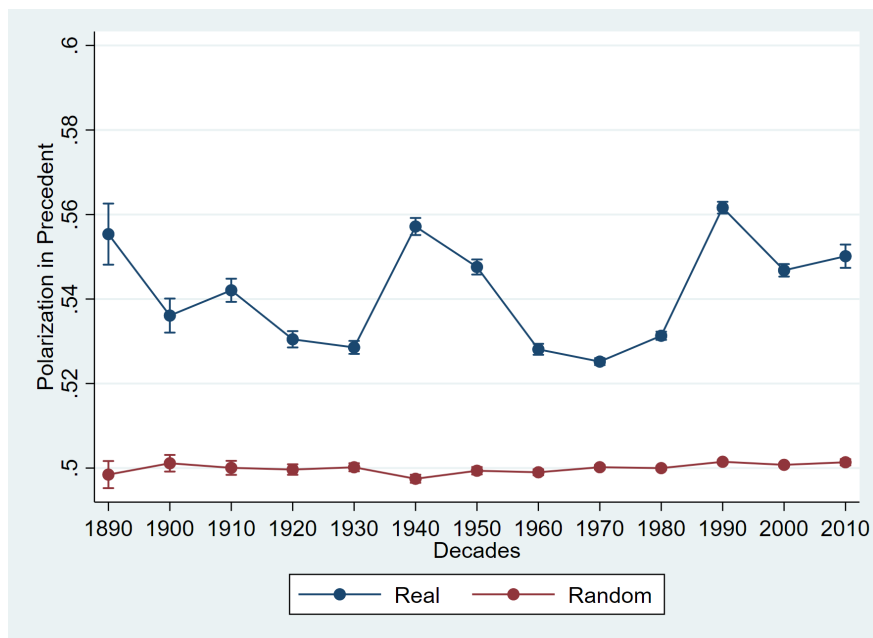


Figure 2: Polarization in Precedents in U.S. Circuit Courts

*Notes:* Polarization measures over time in U.S. Circuit Courts, 1891-2013 for citations. The blue line gives the average polarization in the true dataset. The red line gives the average polarization in the shuffled dataset (random party affiliations). Error bars indicate the 99% confidence interval.

### 3.2 Polarization in Reasoning or Decision when judges are under greater scrutiny

In this section, we examine how judicial reasoning in prose and precedents evolve under scenarios of increased judicial scrutiny. We hypothesize that when judges face such scrutiny particularly in politically diverse settings they may suppress overt expressions of motivated reasoning in their written opinions, even if their final decisions (as reflected in voting behavior) remain polarized. To examine this, we analyze both judicial prose and precedent citations, as well as voting patterns, which have consistently demonstrated partisan tendencies.

## Divided panels

Our investigation begins with how judicial reasoning and decisions are influenced when judges serve on a three-member panel that consists of both Republican and Democratic appointees. According to [Thaler \(2020\)](#)s framework, motivated reasoning occurs when individuals process information in a way that aligns with their prior beliefs, especially in politically charged environments. In judicial settings, motivated reasoning would predict that judges are likely to favor legal interpretations that support their political ideology. However, when judges are part of politically divided panels, they face heightened scrutiny from colleagues with opposing ideological views. This scrutiny leads to two distinct but connected effects: it moderates how judges express their reasoning in written opinions, but it does not eliminate ideological disagreements, which manifest as dissenting votes.

Judges under scrutiny may temper their written opinions to avoid overt expressions of partisanship that could be easily criticized by opposing panel members. This occurs because the diverse panel composition forces judges to justify their legal reasoning in a way that can withstand scrutiny from colleagues with different ideological viewpoints. As a result, we observe a reduction in polarization in the language and legal citations of their opinions.

However, while motivated reasoning may be constrained in the written text, ideological differences still exist at a deeper level. These differences are harder to suppress in the final decision-making process, which often results in dissenting votes. Dissent, in this case, becomes a way for judges to express their underlying political beliefs when they cannot fully align with the majority opinion. Voting behavior, unlike written opinions, is less subject to the same degree of scrutiny because it is a direct reflection of each judges individual stance on the case outcome. Therefore, even though judges moderate their reasoning to align with doctrinal standards under scrutiny, they are still likely to cast dissenting votes when their core ideological beliefs diverge from the majority. Moreover, previous studies indicate that political divisions within a panel creates an opportunity for whistleblowing, through dissenting opinions, to expose disobedient decision-making by the major-

ity. In the presence of such a whistleblower, the majority must sometimes capitulate and keep its decision within the confines of doctrine [Cross and Tiller \(1997\)](#); [Beim et al. \(2021\)](#); [Cohen \(2023\)](#).

To explore these dynamics, we employ a linear regression model that examines polarization in judicial reasoning and dissenting votes, with the key independent variable being participation in a politically divided panel. The counterfactual group consists of judges participating in politically homogeneous panels. This model controls for Circuit  $\times$  Year and legal issues fixed effects. In [Table 2](#), we also look at the scenario of whether a judge sitting on a divided panel is a minority judge in terms of political affiliations. In this situation, heightened scrutiny will lead to even greater moderation in reasoning, considering the composition of the panel.

[Tables 1 and 2](#) show that judges are more likely to cast dissenting votes when they are part of a divided panel or as a minority member within such a panel. Concurrently, our findings indicate a reduced degree of motivated reasoning in their prose and precedent citations, aligning with our hypothesis. Compared to the previous literature on congressional speech [Gentzkow et al. \(2019\)](#) where the polarization variation is only 0.015, the dampening effect we observe is large.

Table 1: Polarization in Divided Panels

|                          | (1)<br>Text          | (2)<br>Citation      | (3)<br>Dissent vote |
|--------------------------|----------------------|----------------------|---------------------|
| Divided Panel            | -0.032***<br>(0.005) | -0.038***<br>(0.004) | 0.006***<br>(0.001) |
| Observations             | 310604               | 269155               | 1030343             |
| $R^2$                    | 0.335                | 0.125                | 0.009               |
| Circuit $\times$ Year FE | ✓                    | ✓                    | ✓                   |
| Legal Issue FE           | ✓                    | ✓                    | ✓                   |

*Notes:* This table shows how judges on a divided panel would exhibit polarization in prose, precedent, and policy. The unit of observation for Column (1) and (2) is at the opinion level, and Column (3) is at the vote level. Every case has three votes from three judges sitting in a panel and judges are allowed to write concurring or dissent opinions besides the majority opinion for each case. We controlled for Circuit  $\times$  Year and legal issues fixed effects. Standard errors clustered at judge level in parentheses. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$



Table 2: Polarization in Divided Panels

|                          | Text<br>(1)          | Citation<br>(2)      | Dissent Vote<br>(3) |
|--------------------------|----------------------|----------------------|---------------------|
| Minority                 | -0.020***<br>(0.006) | -0.030***<br>(0.004) | 0.012***<br>(0.001) |
| Observations             | 225817               | 196097               | 742495              |
| $R^2$                    | 0.320                | 0.065                | 0.012               |
| Circuit $\times$ Year FE | ✓                    | ✓                    | ✓                   |
| Legal Issue FE           | ✓                    | ✓                    | ✓                   |

*Notes:* Effect of being a minority judge (D of DRR or R of RDD) on the polarization in texts and citations, and the likelihood to cast a dissenting vote, controlling for Circuit  $\times$  Year and legal issues fixed effects. The unit of observation for Column (1) and (2) is at the opinion level, and Column (3) is at the vote level. Standard errors clustered at judge level in parentheses. The sample is cases with judges from both political parties.

\* $p < .1$ , \*\* $p < 0.05$ , \*\*\* $p < .01$ .

## Electoral Cycles

We observe a similar pattern in another scenario of scrutiny, namely, the periods leading up to Presidential and midterm elections. With heightened scrutiny, we may expect a decrease in polarization with their reasoning. To investigate this hypothesis, we divided the time into 16 quarters preceding a Presidential election. Our analysis focuses on the electoral cycles and their impact on polarization in judicial reasoning. The results of this analysis are detailed in Table 3.

We find that judges reduce polarization in both the texts of opinions and citations preceding midterm elections, indicating a notable shift in judicial behavior during these periods. This trend contrasts with the pattern observed before Presidential elections, where such polarization does not exhibit a significant change. A plausible explanation for this discrepancy can be linked to the heightened partisan political priming associated with Presidential elections. According to [Chen \(2024\)](#), this kind of priming is intense during Presidential elections, potentially neutralizing the judges' inclination to reduce polarization under scrutiny.

The argument for reduced polarization near elections hinges on the heightened scrutiny that judges face during these periods. Key stakeholders such as political actors, legal professionals, and

the media closely observe judicial decisions, especially when those decisions could have broader political ramifications. This scrutiny creates indirect pressure on judges to appear impartial or less overtly partisan, even if they are not directly elected. Moreover, the political environment in which judges operate may heighten their awareness of how their rulings align with party politics. As a result, judges may strategically temper their reasoning to avoid potential accusations of partisanship or political backlash, particularly during high-stakes periods like elections. This tendency helps explain the reduction in polarization we observe in judicial opinions and citations, particularly leading up to midterm elections, when such scrutiny may be most intense.

Furthermore, an intriguing pattern emerges in the context of both midterm and Presidential elections as they draw near: an increase in dissenting votes. This observation, documented in Column 5, aligns with what can be described as a ‘whistleblowing effect’ similar to that found on politically divided panels. During periods of increased scrutiny, which are common around election times, judges might express dissent more openly, a behavior that is consistent with a whistleblowing response.

To summarize, we investigate two different situations of increased scrutiny, which prior research has suggested can lead to greater dissent in votes. While our analysis confirmed this finding, we observe a reduction in polarization in prose and citations to precedent at the same time. Such a response suggests a complex interplay between the political environment and judicial decision-making, that judges will tend to exhibit partisanship in decisions rather than in reasoning.

To address concerns around non-random assignment, we have performed robustness checks by excluding the Second, Eighth, Ninth, and D.C. Circuits, which previous research identifies as potentially less random in panel assignments [Chilton and Levy \(2015\)](#). Our findings remain consistent even after these exclusions, shown in Table 8 and 9. Furthermore, [Chen et al. \(2016\)](#) provides evidence suggesting that panel compositions do not exhibit time-based autocorrelation, further reinforcing the validity of this assumption. We are also aware that within-panel dynamics could influence opinion content. However, we conduct robustness checks focused on senior judges

Table 3: Electoral Cycles in Text and Citation

|                          | (1)                  | (2)                 | (3)                | (4)                 | (5)                |
|--------------------------|----------------------|---------------------|--------------------|---------------------|--------------------|
|                          | Prose                |                     | Precedents         |                     | Dissent Vote       |
|                          | All Op               | Dis Op              | All Op             | Dis Op              |                    |
| Quarter to election=1    | 0.004<br>(0.005)     | -0.019<br>(0.013)   | -0.002<br>(0.003)  | 0.007<br>(0.006)    | 0.005**<br>(0.002) |
| Quarter to election=2    | 0.005<br>(0.004)     | -0.021<br>(0.013)   | 0.003<br>(0.002)   | 0.001<br>(0.006)    | 0.003*<br>(0.002)  |
| Quarter to election=3    | 0.009**<br>(0.004)   | -0.003<br>(0.011)   | 0.004**<br>(0.002) | 0.002<br>(0.006)    | 0.003*<br>(0.002)  |
| Quarter to election=4    | 0.010**<br>(0.004)   | -0.019<br>(0.013)   | 0.001<br>(0.002)   | -0.014**<br>(0.006) | -0.001<br>(0.002)  |
| Quarter to election=5    | 0.010*<br>(0.006)    | 0.004<br>(0.017)    | -0.001<br>(0.003)  | -0.010<br>(0.008)   | 0.002<br>(0.002)   |
| Quarter to election=6    | 0.005<br>(0.006)     | -0.006<br>(0.017)   | 0.000<br>(0.003)   | -0.011<br>(0.008)   | 0.001<br>(0.002)   |
| Quarter to election=7    | 0.006<br>(0.006)     | 0.008<br>(0.017)    | -0.001<br>(0.002)  | -0.008<br>(0.008)   | -0.001<br>(0.002)  |
| Quarter to election=8    | -0.008*<br>(0.005)   | -0.025<br>(0.015)   | -0.002<br>(0.002)  | -0.019**<br>(0.007) | 0.001<br>(0.002)   |
| Quarter to election=9    | -0.012**<br>(0.006)  | 0.001<br>(0.019)    | -0.002<br>(0.003)  | -0.018**<br>(0.009) | 0.005*<br>(0.002)  |
| Quarter to election=10   | -0.012**<br>(0.006)  | -0.009<br>(0.019)   | -0.001<br>(0.003)  | -0.021**<br>(0.009) | 0.003<br>(0.002)   |
| Quarter to election=11   | -0.006<br>(0.005)    | -0.010<br>(0.019)   | 0.000<br>(0.003)   | -0.016*<br>(0.009)  | 0.003<br>(0.002)   |
| Quarter to election=12   | -0.011***<br>(0.004) | -0.015<br>(0.013)   | -0.003<br>(0.002)  | -0.010<br>(0.006)   | -0.001<br>(0.002)  |
| Quarter to election=13   | -0.003<br>(0.005)    | -0.021<br>(0.015)   | 0.000<br>(0.002)   | -0.004<br>(0.007)   | 0.000<br>(0.002)   |
| Quarter to election=14   | -0.009*<br>(0.005)   | -0.031**<br>(0.015) | 0.000<br>(0.002)   | -0.000<br>(0.007)   | -0.002<br>(0.002)  |
| Quarter to election=15   | -0.002<br>(0.004)    | -0.021<br>(0.013)   | 0.002<br>(0.002)   | 0.003<br>(0.006)    | -0.002<br>(0.002)  |
| Observations             | 190135               | 17110               | 178609             | 13494               | 606999             |
| $R^2$                    | 0.243                | 0.137               | 0.097              | 0.086               | 0.008              |
| Circuit $\times$ Year FE | ✓                    | ✓                   | ✓                  | ✓                   | ✓                  |
| Season FE                | ✓                    | ✓                   | ✓                  | ✓                   | ✓                  |
| Legal Issue FE           | ✓                    | ✓                   | ✓                  | ✓                   | ✓                  |

Notes: The unit of observation for Column (1) to (4) is at the opinion level, and Column (5) is at the vote level. Standard errors clustered at judge level in parentheses. The base period is 16 quarters to Presidential Elections. The sample is cases published after 1975. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

who oversee opinion assignments to account for potential multi-judge influence, shown in Table 10 and 11. Our results remain consistent, supporting our assumption that we can attribute opinion text predominantly to a single judge.

### 3.3 Polarization and Promotion Incentives

In this section, we analyze an institutional factor that is likely to influence political polarization in the courts: promotion incentives. We concentrate on the nomination process for Supreme Court of the United States (SCOTUS) justices, where Circuit Court judges are potential candidates for elevation to the highest court by presidential and senate appointment. This scenario raises a question: do judges demonstrate increased partisan polarization in their reasoning and decision-making as a strategy to secure a nomination? Drawing on the findings of Black and Owens (2016), who observed that judges on the president’s “shortlist” are more likely to write dissent opinions and vote in line with the presidents, our analysis seeks to understand if politically motivated reasoning might change with SCOTUS vacancies using a much larger sample of judges and years. Detailed methodology and data processing information for this analysis are provided in the SI appendix.

In Table 4, we present our results using the same specification as in Table 1. The results indicates no systematic differences between judges on the presidential shortlist and their non-contender counterparts; moreover, a Supreme Court vacancy does not result in significant changes in behavior across the entire judicial spectrum in Circuit Courts. However, during a Supreme Court vacancy, contender judges demonstrate noticeably more polarization in their selection of legal precedents. Nevertheless, we observe no significant extension of this trend to their writing style or voting patterns, which differs from Black and Owens (2016), whom observed a significant effect for dissent votes for contenders. From a theoretical standpoint, it is remarkable that contender judges choose to stand out to a potential nominating president through their citations to precedent, which we previously documented to be less polarizing in general. Presidents may look to nominate partisan/ideological allies rather than individuals that are politically ambiguous or moderate in their

behavior in how they follow precedents. The finding here suggests that the reasoning process of judges, just like decisions, might also be strategic, depending on interests and scrutiny involved.

Table 4: Polarization in SCOTUS Vacancies

|                             | Text<br>(1)       | Citation<br>(2)    | Dissent Vote<br>(3) |
|-----------------------------|-------------------|--------------------|---------------------|
| Vacancy                     | -0.001<br>(0.003) | -0.001<br>(0.001)  | 0.000<br>(0.001)    |
| Contenders                  | -0.041<br>(0.039) | -0.005<br>(0.021)  | 0.003<br>(0.005)    |
| Vacancy $\times$ Contenders | 0.016<br>(0.019)  | 0.017**<br>(0.008) | -0.001<br>(0.006)   |
| Observations                | 49,711            | 46,759             | 153,672             |
| $R^2$                       | 0.257             | 0.100              | 0.008               |
| Circuit $\times$ Year FE    | ✓                 | ✓                  | ✓                   |
| Legal Issue FE              | ✓                 | ✓                  | ✓                   |

Standard errors in parentheses

\*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

*Notes:* Effect of being a SCOTUS vacancy contender on the polarization in texts and citations, and the likelihood to cast a dissenting vote, controlling for Circuit  $\times$  Year and legal issues fixed effects. The unit of observation for Column (1) and (2) is at opinion level, and Column (3) at the vote level. Standard errors clustered at judge level in parentheses. Sample is cases with judges from both political parties after 1975. \* $p < .1$ , \*\* $p < 0.05$ , \*\*\* $p < .01$ .

## 4 Conclusion

Judges are nominally expected to sit above the partisan fray. However, we find they are divisive in their rhetoric and citations to legal precedent. We find that both text and citations display polarization, with text being even more polarized. In addition, judges display less polarization in reasoning when under greater scrutiny, sitting on divided panels, or before elections. Collectively, these findings suggest a divergence in how judges approach their reasoning and decision-making processes, reflecting varying degrees of partisanship under different circumstances.

Lifetime-appointed judges assert that their decisions are not influenced by politics. However, their voting trends and the intense partisan struggles during confirmation processes suggest otherwise. Our findings reveal the political nature of judicial reasoning measured in their rhetoric and

their citations to precedent. If judges cherry-pick their precedents, this casts a shadow over the fairness of their decisions. A diminished sense of legitimacy can lead to decreased compliance with the law, which can have social and economic implications. Trust has been shown to have impacts, see [Acemoglu et al. \(2020\)](#)s recent paper documenting this link causally. They show that enhanced trust spurs reliance on formal institutions. Reliance on formal institutions can, in turn, propel economic development, investments, and entrepreneurial undertakings. While our paper may not directly quantify these effects, it seeks to underscore their significance.

## References

- Acemoglu, Daron, Ali Cheema, Asim I Khwaja, and James A Robinson**, “Trust in state and nonstate actors: Evidence from dispute resolution in Pakistan,” *Journal of Political Economy*, 2020, 128 (8), 3090–3147. [22](#)
- Beim, Deborah, Tom S Clark, and Benjamin E Lauderdale**, “Republican-majority appellate panels increase execution rates for capital defendants,” *The Journal of Politics*, 2021, 83 (3), 1163–1167. [4](#), [16](#)
- Belloni, Alexandre, Daniel Chen, Victor Chernozhukov, and Christian Hansen**, “Sparse models and methods for optimal instruments with an application to eminent domain,” *Econometrica*, 2012, 80 (6), 2369–2429. [4](#)
- Bénabou, Roland and Jean Tirole**, “Mindful economics: The production, consumption, and value of beliefs,” *Journal of Economic Perspectives*, 2016, 30 (3), 141–64. [2](#)
- Berdej6, Carlos and Daniel L Chen**, “Electoral cycles among us courts of appeals judges,” *The Journal of Law and Economics*, 2017, 60 (3), 479–496. [7](#), [9](#)
- Berger, Raoul**, *Government by judiciary*, Liberty Fund, 1997. [3](#)
- Bertrand, Marianne and Emir Kamenica**, “Coming Apart? Cultural Distances in the United States over Time,” Working Paper 24771, National Bureau of Economic Research June 2018. [12](#)
- , **Francis Kramarz, Antoinette Schoar, and David Thesmar**, “The cost of political connections,” *Review of Finance*, 2018, 22 (3), 849–876. [6](#), [8](#), [30](#)
- Black, Ryan C and Ryan J Owens**, “Courting the president: how circuit court judges alter their behavior for promotion to the Supreme Court,” *American Journal of Political Science*, 2016, 60 (1), 30–43. [20](#), [32](#)
- Bonica, Adam and Maya Sen**, “Estimating judicial ideology,” *Journal of Economic Perspectives*, 2021, 35 (1), 97–118. [4](#), [6](#)

- Braman, Eileen**, “Reasoning on the threshold: Testing the separability of preferences in legal decision making,” *The Journal of Politics*, 2006, 68 (2), 308–321. [3](#)
- **and Thomas E Nelson**, “Mechanism of motivated reasoning? Analogical perception in discrimination disputes,” *American Journal of Political Science*, 2007, 51 (4), 940–956. [3](#)
- Camacho-collados, Jose, Kiamehr Rezaee, Talayeh Riahi, Asahi Ushio, Daniel Loureiro, Dimosthenis Antypas, Joanne Boisson, Luis Espinosa Anke, Fangyu Liu, Eugenio Martínez Cámara et al.**, “TweetNLP: Cutting-Edge Natural Language Processing for Social Media,” in “Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing: System Demonstrations” Association for Computational Linguistics Abu Dhabi, UAE December 2022, pp. 38–49. [29](#)
- Chen, Daniel L**, “Priming ideology I: Why do presidential elections affect US judges,” *European Economic Review*, 2024, 169, 104835. [13](#), [17](#)
- **, Vardges Levonyan, and Susan Yeh**, “Can policies affect preferences: evidence from random variation in abortion jurisprudence,” *TSE Working Paper*, 2016. [18](#)
- Chen, Tianqi and Carlos Guestrin**, “Xgboost: A scalable tree boosting system,” in “Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining” ACM 2016, pp. 785–794. [30](#)
- Chilton, Adam S and Marin K Levy**, “Challenging the Randomness of Panel Assignment in the Federal Courts of Appeals,” *Cornell L. Rev.*, 2015, 101, 1. [18](#)
- Choi, Stephen J and G Mitu Gulati**, “Bias in judicial citations: a window into the behavior of judges?,” *The Journal of Legal Studies*, 2008, 37 (1), 87–129. [7](#)
- Cohen, Alma**, “The Pervasive Influence of Ideology at the Federal Circuit Courts,” Technical Report, National Bureau of Economic Research 2023. [4](#), [16](#)
- Cross, Frank B and Emerson H Tiller**, “Judicial partisanship and obedience to legal doctrine: Whistleblowing on the federal courts of appeals,” *Yale LJ*, 1997, 107, 2155. [7](#), [16](#)
- Dahl, Gordon B, Andreas Ravndal Kostøl, and Magne Mogstad**, “Family welfare cultures,”



- The Quarterly Journal of Economics*, 2014, 129 (4), 1711–1752. [4](#)
- David, H, Nicole Maestas, Kathleen J Mullen, and Alexander Strand**, “Does delay cause decay? The effect of administrative decision time on the labor force participation and earnings of disability applicants,” Technical Report, National Bureau of Economic Research 2015. [4](#)
- Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova**, “Bert: Pre-training of deep bidirectional transformers for language understanding,” *arXiv preprint arXiv:1810.04805*, 2018. [11](#), [29](#)
- Doerfler, Ryan and Samuel Moyn**, “Democratizing the Supreme Court,” Technical Report 2020. [3](#)
- Epley, Nicholas and Thomas Gilovich**, “The mechanics of motivated reasoning,” *Journal of Economic perspectives*, 2016, 30 (3), 133–40. [2](#)
- Firth, John R**, “A synopsis of linguistic theory, 1930-1955,” *Studies in linguistic analysis*, 1957. [11](#)
- Förster, Jens, Nira Liberman, and E Tory Higgins**, “Accessibility from active and fulfilled goals,” *Journal of Experimental Social Psychology*, 2005, 41 (3), 220–239. [2](#)
- Gennaioli, Nicola and Andrei Shleifer**, “Judicial fact discretion,” *The Journal of Legal Studies*, 2008, 37 (1), 1–35. [8](#)
- Gentzkow, Matthew, Jesse M Shapiro, and Matt Taddy**, “Measuring Group Differences in High-Dimensional Choices: Method and Application to Congressional Speech,” *Econometrica*, 2019, 87 (4), 1307–1340. [6](#), [8](#), [12](#), [13](#), [16](#)
- Grover, Aditya and Jure Leskovec**, “node2vec: Scalable feature learning for networks,” in “Proceedings of the 22nd ACM SIGKDD international conference on Knowledge discovery and data mining” 2016, pp. 855–864. [11](#)
- Haidt, Jonathan**, “The Positive emotion of elevation.,” *Prevention & Treatment*, 2000, 3 (1). [2](#)
- Hasen, Richard L**, “Polarization and the Judiciary,” *Annual Review of Political Science*, 2019, 22, 261–276. [6](#), [14](#)

- Hirschl, Ran**, *Towards juristocracy: the origins and consequences of the new constitutionalism*, Harvard University Press, 2009. [3](#)
- Jelveh, Zubin, Bruce Kogut, and Suresh Naidu**, “Political language in economics,” Technical Report 14-57 2018. [6](#)
- Jensen, Jacob, Suresh Naidu, Ethan Kaplan, Laurence Wilse-Samson, David Gergen, Michael Zuckerman, and Arthur Spirling**, “Political polarization and the dynamics of political language: Evidence from 130 years of partisan speech [with comments and discussion],” *Brookings Papers on Economic Activity*, 2012, pp. 1–81. [6](#)
- Kahan, Dan M**, “Ideology, motivated reasoning, and cognitive reflection,” *Judgment and Decision Making*, 2013, 8 (4), 407–424. [2](#)
- , “The politically motivated reasoning paradigm, part 1: What politically motivated reasoning is and how to measure it,” *Emerging trends in the social and behavioral sciences: An interdisciplinary, searchable, and linkable resource*, 2016, pp. 1–16. [3](#), [8](#)
- , **David Hoffman, Danieli Evans, Neal Devins, Eugene Lucci, and Katherine Cheng**, “Ideology or situation sense: an experimental investigation of motivated reasoning and professional judgment,” *U. Pa. L. Rev.*, 2015, 164, 349. [3](#)
- Kling, Jeffrey R**, “Incarceration length, employment, and earnings,” *American Economic Review*, 2006, 96 (3), 863–876. [4](#)
- Levinson, Sanford**, *Our undemocratic Constitution: Where the Constitution goes wrong (and how we the people can correct it)*, Oxford University Press, 2006. [3](#)
- Levy, Marin K**, “Panel assignment in the federal courts of appeals,” *Cornell L. Rev.*, 2017, 103, 65. [8](#)
- Mendels, Omri, Coby Peled, Nava Vaisman Levy, Tomer Rosenthal, Limor Lahiani et al.**, “Microsoft Presidio: Context aware, pluggable and customizable PII anonymization service for text and images,” 2018. [11](#)
- Mueller-Smith, Michael**, “The criminal and labor market impacts of incarceration,” Technical

Report 2015. [4](#)

**Nemacheck, Christine L**, *Strategic Selection: Presidential Nomination of Supreme Court Justices from Herbert Hoover through George W. Bush*, University of Virginia Press, 2007. [32](#)

**Niblett, Anthony and Albert H Yoon**, “Friendly precedent,” *William and Mary Law Review*, 2016, 57 (5), 1789–1824. [7](#)

**Sanh, Victor, Lysandre Debut, Julien Chaumond, and Thomas Wolf**, “DistilBERT, a distilled version of BERT: smaller, faster, cheaper and lighter,” *arXiv preprint arXiv:1910.01108*, 2019. [29](#)

**Schmitt, Carl**, *Gesetz und Urteil: Eine Untersuchung zum Problem der Rechtspraxis*, Beck, 1969. [3](#)

—, “The Crisis of Parliamentary Democracy [1923],” *Trans. E. Kennedy*, 1985. [3](#)

—, *Political theology: Four chapters on the concept of sovereignty*, University of Chicago Press, 2005. [3](#)

**Simon, Dan and Nicholas Scurich**, “Judicial Overstating,” in “Published in Special Symposium: The Supreme Court and the American Public,” Vol. 88 2014, pp. 14–36. [14](#)

**Songer, Donald R.**, *The United States Courts of Appeals Data Base Documentation for Phase 1*  
Last visited June 20, 2018. [10](#)

**Sood, Avani Mehta**, “Motivated Cognition in Legal JudgmentsAn Analytic Review,” *Annual Review of Law and Social Science*, 2013, 9, 307–325. [3](#)

**Thaler, Michael**, “The fake news effect: Experimentally identifying motivated reasoning using trust in news,” *arXiv preprint arXiv:2012.01663*, 2020. [3](#), [4](#), [5](#), [15](#)

**Touré-Tillery, Maferima and Ayelet Fishbach**, “How to measure motivation: A guide for the experimental social psychologist,” *Social and Personality Psychology Compass*, 2014, 8 (7), 328–341. [2](#)

**Yang, Zhilin, Zihang Dai, Yiming Yang, Jaime Carbonell, Russ R Salakhutdinov, and Quoc V Le**, “Xlnet: Generalized autoregressive pretraining for language understanding,” *Advances in*

*neural information processing systems*, 2019, 32. [29](#)

**Zeigarnik, Bluma**, “On the retention of completed and uncompleted activities,” *Psychologische Forschung*, 1927, 9, 1–85. [2](#)

# A Training

## A.1 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 [Sanh et al. \(2019\)](#), a smaller version of the BERT model designed to overcome the slow training problem of BERT [Devlin et al. \(2018\)](#) due to the large model size while obtaining similar performance as BERT. Secondly, we use two improved version of BERT, XLnet [Yang et al. \(2019\)](#) and twitter-RoBERTa [Camacho-collados et al. \(2022\)](#) 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 5. 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 5: 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 |

## A.2 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 [Bertrand et al. \(2018\)](#):

- Elastic Net. A 10-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 [Chen and Guestrin \(2016\)](#). 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, as shown in Table [6](#).

Table 6: 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 |

## B Polarization across Time

In this section, 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 3, 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.

## C Polarization by Experience

To explore the underlying mechanism of behavioral anomalies, we examined if such anomalies diminish with experience. Specifically, we focused on whether anomalies are driven by Type I thinking, which may erode with experience, unlike Type II thinking, like motivated reasoning, which are more reflective and intentional. Using the same linear regression framework, we analyzed how polarization in reasoning varies with judges’ experience. Our findings, presented in Table 7, reveal that polarization in prose remains largely unchanged with experience, except for a notable increase among judges with 15 to 25 years of experience. These results suggest that while

judges' experience do not significantly impact polarization in their textual content, their selection of precedents becomes a bit more polarized in the middle of their careers. 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, suggest that the behavioral anomalies are driven by Type II thinking, being more reflective and intentional in nature.

## D Polarization during Vacancies

As noted by [Nemacheck \(2007\)](#), 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 [Black and Owens \(2016\)](#) 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 [Nemacheck \(2007\)](#). Our analytical specification for examining the influence of promotion incentives on judicial polarization is outlined below:

$$Y_{it} = \alpha + \beta \text{Vacancy}_t + \gamma \text{Contender}_i + \delta \text{Vacancy}_t \times \text{Contender}_i + \boldsymbol{\eta}' \mathbf{Z}_{it} + \varepsilon_{it} \quad (1)$$

where  $Y_{it}$  is the polarization outcome (e.g. dissent rate), and  $\mathbf{Z}_{it}$  are Circuit  $\times$  Year and legal-



Table 7: The effect of experience on polarization

|                           | (1)               | (2)                  |
|---------------------------|-------------------|----------------------|
|                           | Text              | Citation             |
| Age                       | -0.000<br>(0.001) | -0.001***<br>(0.001) |
| Experience $\in [5, 10)$  | -0.000<br>(0.005) | 0.004<br>(0.003)     |
| Experience $\in [10, 15)$ | -0.008<br>(0.010) | -0.001<br>(0.006)    |
| Experience $\in [15, 20)$ | -0.002<br>(0.016) | 0.017*<br>(0.009)    |
| Experience $\in [20, 25)$ | -0.005<br>(0.021) | 0.025*<br>(0.013)    |
| Experience $\in [25, 30)$ | -0.025<br>(0.027) | 0.010<br>(0.017)     |
| Experience $\in [30, 35)$ | -0.030<br>(0.033) | -0.007<br>(0.022)    |
| Experience $\in [35, 55)$ | -0.039<br>(0.042) | -0.018<br>(0.032)    |
| Observations              | 312930            | 271059               |
| $R^2$                     | 0.334             | 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.  
 $*p < .1$ ,  $**p < 0.05$ ,  $***p < .01$ .

issue fixed effects. We estimate the equation using OLS with robust standard errors clustered by individual judge. The coefficient of primary interest is  $\delta$ , which measures the average difference in the polarization outcome, accounting for the fixed effects, for contenders during the periods of judicial vacancies.

## E Robustness checks

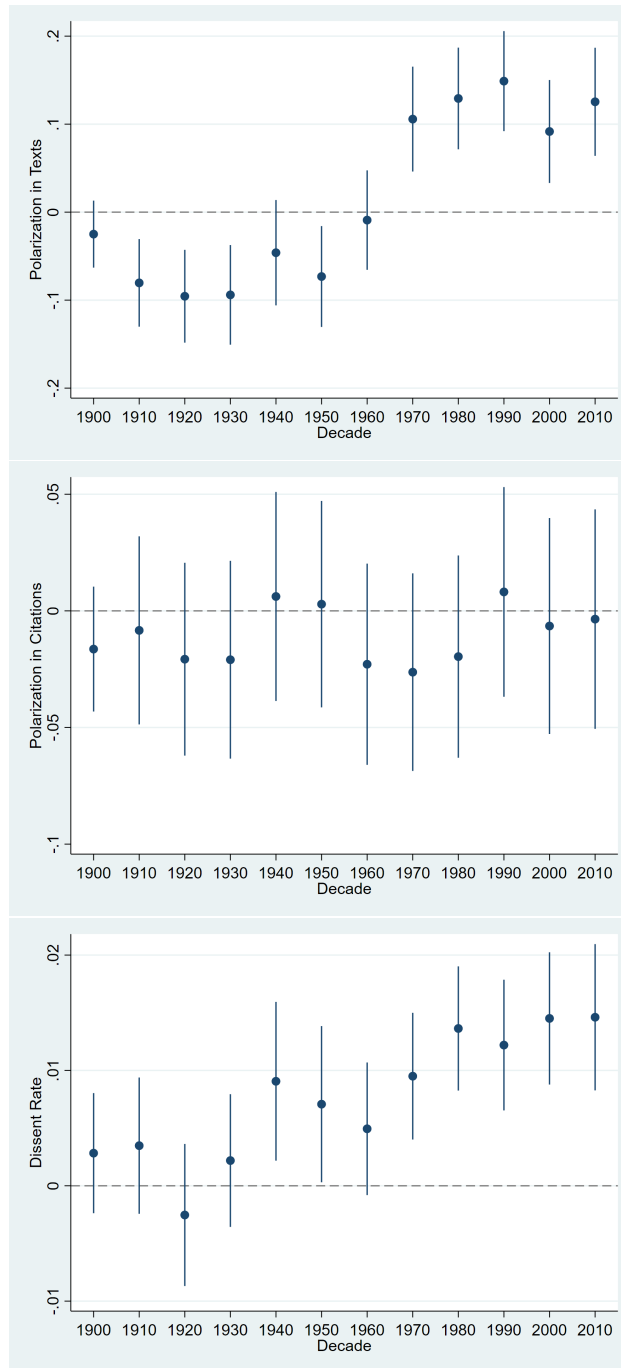


Figure 3: Polarization in prose, Precedent, and Policy across time

*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 8: Polarization in Divided Panels (Dropping Court 2, 8, 9, and DC)

|                          | (1)<br>Text          | (2)<br>Citation      | (3)<br>Dissent vote |
|--------------------------|----------------------|----------------------|---------------------|
| Divided Panel            | -0.034***<br>(0.007) | -0.041***<br>(0.005) | 0.004***<br>(0.001) |
| Observations             | 178396               | 154920               | 598232              |
| $R^2$                    | 0.306                | 0.123                | 0.011               |
| Circuit $\times$ Year FE | ✓                    | ✓                    | ✓                   |
| Legal Issue FE           | ✓                    | ✓                    | ✓                   |

*Notes:* This table shows how judges on a divided panel would exhibit polarization in prose, precedent, and policy. The unit of observation for Column (1) and (2) is at the opinion level, and Column (3) is at the vote level. Every case has three votes from three judges sitting in a panel and judges are allowed to write concurring or dissent opinions besides the majority opinion for each case. We controlled for Circuit  $\times$  Year and legal issues fixed effects. Standard errors clustered at judge level in parentheses. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table 9: Polarization in Divided Panels (Dropping Court 2, 8, 9, and DC)

|                          | Text<br>(1)         | Citation<br>(2)      | Dissent Vote<br>(3) |
|--------------------------|---------------------|----------------------|---------------------|
| Minority                 | -0.018**<br>(0.008) | -0.030***<br>(0.005) | 0.009***<br>(0.001) |
| Observations             | 129135              | 112337               | 426877              |
| $R^2$                    | 0.295               | 0.068                | 0.013               |
| Circuit $\times$ Year FE | ✓                   | ✓                    | ✓                   |
| Legal Issue FE           | ✓                   | ✓                    | ✓                   |

*Notes:* Effect of being a minority judge (D of DRR or R of RDD) on the polarization in texts and citations, and the likelihood to cast a dissenting vote, controlling for Circuit  $\times$  Year and legal issues fixed effects. The unit of observation for Column (1) and (2) is at the opinion level, and Column (3) is at the vote level. Standard errors clustered at judge level in parentheses. The sample is cases with judges from both political parties. \* $p < .1$ , \*\* $p < 0.05$ , \*\*\* $p < .01$ .

Table 10: Polarization in Divided Panels (Senior judges)

|                          | (1)<br>Text          | (2)<br>Citation      | (3)<br>Dissent vote |
|--------------------------|----------------------|----------------------|---------------------|
| Divided Panel            | -0.046***<br>(0.007) | -0.047***<br>(0.005) | 0.007***<br>(0.002) |
| Observations             | 100726               | 87842                | 327994              |
| $R^2$                    | 0.356                | 0.206                | 0.014               |
| Circuit $\times$ Year FE | ✓                    | ✓                    | ✓                   |
| Legal Issue FE           | ✓                    | ✓                    | ✓                   |

*Notes:* This table shows how judges on a divided panel would exhibit polarization in prose, precedent, and policy. The unit of observation for Column (1) and (2) is at the opinion level, and Column (3) is at the vote level. Every case has three votes from three judges sitting in a panel and judges are allowed to write concurring or dissent opinions besides the majority opinion for each case. We controlled for Circuit  $\times$  Year and legal issues fixed effects. Standard errors clustered at judge level in parentheses. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table 11: Polarization in Divided Panels (Senior judges)

|                          | Text<br>(1)          | Citation<br>(2)      | Dissent Vote<br>(3) |
|--------------------------|----------------------|----------------------|---------------------|
| Minority                 | -0.036***<br>(0.008) | -0.045***<br>(0.005) | 0.016***<br>(0.002) |
| Observations             | 100726               | 87842                | 327994              |
| $R^2$                    | 0.354                | 0.207                | 0.015               |
| Circuit $\times$ Year FE | ✓                    | ✓                    | ✓                   |
| Legal Issue FE           | ✓                    | ✓                    | ✓                   |

*Notes:* Effect of being a minority judge (D of DRR or R of RDD) on the polarization in texts and citations, and the likelihood to cast a dissenting vote, controlling for Circuit  $\times$  Year and legal issues fixed effects. The unit of observation for Column (1) and (2) is at the opinion level, and Column (3) is at the vote level. Standard errors clustered at judge level in parentheses. The sample is cases with judges from both political parties. \* $p < .1$ , \*\* $p < 0.05$ , \*\*\* $p < .01$ .