Decision in Question:

A Study of Supreme Court Justices' Accusations of Judicial Activism in Separate Opinions

Peter Bachman [*,†]

January 16, 2024

How do justices decide what to include in separate opinions? Text-as-data methods introduced a number of linguistic features Justices utilize when writing opinions, yet these measures do not look at the substance of opinions. I focus on when separate opinions claim a majority coalition engages in *judicial activism*, or violates long-held traditions of *judicial restraint*. I theorize that Justices view arguments in separate opinions as informational cues to those who read them, ascribing costs and values to each argument type. Under this framework, Justices view *judicial activism* as cue with high value due to the information it provides policy implementors, and place even more value in these allegations when the majority opinion diverges from their own preferences. Yet due to the negative connotation of *judicial activism* among the public, hese allegations come with higher costs in cases likely to gain media coverage. To better understand when justices decide to allegations of *judicial activims*, I measure the likelihood that 6,925 separate opinions from 1945 to 2014 contain allegations of *judicial activism* by fine-tuning a Large Language Model, and modeling the likelihood Justices make criticism of *judicial activism* using a two-stage selection model. The results provide mixed support for my theory, leading to questions about the downstream effects of these allegations, as well as alternative substantive aspects of Supreme Court opinions.

[*] Washington University in St. Louis, Department of Political Science, bachman.p@wustl.edu
[†] The author is grateful for the helpful feedback from Jim Spriggs, Ted Enamorado, the Third-Year Paper Workshop, Political Science Data Lab, and the American Politics Workshop.

> "To be able to write an opinion solely for oneself, without the need to accommodate, to any degree whatever, the more-or-less differing views of one's colleagues; to address precisely the points of law that one considers important and no others; to express precisely the degree of quibble, or foreboding, or disbelief, or indignation that one believes the majority's disposition should engender—that is indeed an unparalleled pleasure." (Scalia 1994)

Separate opinions are often written "for the intelligence of a future day," (Ginsburg 2010, quoting Charles Hughes) with the hope that future Justices will change policy in favor of the separate opinion writer's preferences. One reason Justices write separate opinions is to highlight flaws in the majority opinion (Wahlbeck, Spriggs, and Maltzman 1999) as an attempt to limit the decision's power. By highlighting the flaws of a decision, separate opinions signal uncertainty in the best policy implementation. Prior research suggests separate opinions are successful in these attempts, resulting in lower courts interpreting a decision negatively to restrict the application of said decision (Baum 1978; Danelski 1967; Hansford and Spriggs 2018; Johnson 1979, 1987). Justices may also use separate opinions in an attempt to bargain with the majority opinion (J. R. Lax and Cameron 2007; Jeffrey R. Lax and Rader 2015) in an attempt to sway policy towards their own preferences. Yet not all separate opinions are created equal (Westerland et al. 2010), suggesting that something within the language of these opinions may influence legal development, rather than only the presence of a separte opinion. How then do justices decide what to include in separate opinions? In this paper I explore when Justices write separate opinions and claim the majority coalition engaged in *judicial activism*, violating long held traditions of how Justices are expected to decide cases.

In understanding what Justices decide to include when writing opinions, research suggests linguistic features of opinions influence legal development. Linguistic features can get the attention of others, whether future Justices, lower court judges, or the public (Black et al. 2016). Emotional language is used often to gain the attention of the media (Bryan and Ringsmuth 2016; Hinkle and Nelson 2017) or the attention of future Justices (P. C. Corley, Steigerwalt, and Ward 2023), and the clarity with which an opinion is written can influence its implementation (Black et al. 2016; Hinkle et al. 2012; Nelson and Hinkle 2018). Linguistic traits of opinions, the way Justices write, are important, but the substance of opinions is important in how Justices pursue their policy preferences. Some research attempts to look at how Justices (Rice 2017), or litigants (Wedeking 2010) reframe arguments to get preferable outcomes. Separate opinions can help lower court judges (Nelson and Hinkle 2018; Westerland et al. 2010), future Justices (Black and Spriggs II 2013; Hansford and Spriggs 2018), policy implementors (Spriggs 1996) know how to interpret precedent and form law, as well as influence public support for a decision (Zink, Spriggs, and Scott 2009). Yet resultes are mixed on how much these features in opinions matter, and how they influence actors within and without the court system. I believe this is due to actors focusing on the arguments, not linguistic traits, found in opinions. Through arguments about how a majority opinion uses certain precedents, jurisprudential approaches, or interprets statutes, justices may hope their separate opinions can result in more favorable policy outcomes in the future.

In this paper I focus on the argument of *judicial activism*. *Judicial activism* is a criticism used when another Justice violates the norm of *judicial restraint*. Justices are expected to follow the judging norm of *judicial restraint* through decide cases in a narrow manner, focusing on changing law as little as possible. *Judicial restraint* often takes the form of deciding a case on the narrowest ruling possible, respecting the previous decisions of the Supreme Court through adhering to precedent regardless of whether they personally agree with it, and respecting policies implemented by the other branches of government. The concept even dates back to the early years of the United States with Thomas Jefferson saying, "one single object, ... [will merit] the endless gratitude of society; that of restraining judges from usurping legislation. And with no body of men is this restraint more wanting than with the judges of what is commonly called our General government" (Thomas Jefferson 1825). As such, *judicial restraint* has been a long-standing norm of the court, creating the expectation that Justices not break from *judicial restraint*. Thus, deviating from *judicial restraint* and engaging in *judicial activism* suggests to those outside of the court that those who decide a case are disregarding foundational norms of the Court. Indeed, *judicial activism* even has a negative connotation to the public, with elected officials often using *judicial activism* as a reason to either avoid nominating justices to the Supreme Court[1] or as a way to highlight the negative impacts of a decision[2]. This gives Justices motivation to highlight when Justices make broader changes to law and violate norms of judging, thus highlighting a flaw in a decision.

I theorize that Justices are focused on shaping law based on their own preferences and treat arguments in separate opinions like informational cues, ascribing allegations of *judicial activism* with high informational value. Because of the strong negative implications tied to *judicial activism* justices believe this allegation high informational value because it is likely to persuade policy implementors to either disregard or scrutinize a decision. Yet media coverage of a case places costs on the use of *judicial activism* allegations because justices value the diffuse support of the court (Gibson and Nelson 2014). Mentions Supreme Court Justices engaging in *judicial activism* may result decreased diffuse support for the Supreme Court, reduce their power to implement future rulings. Yet, the value of these allegations increase as distance between a justice's preferences and the majority coalition's decision increases. In instances where the justices preferences strongly diverge from the majority coalition, justices gain more value in shaping the future implementation of policy in their favor. The value of making *judicial activism* claims also varies based on the type of separate opinion, with dissents having the most value because they disagree with both the decision and rationale of the case. Justices writing concurring opinions are likely to have the least value because concurrences are often written to support the majority's decision with additional reasoning, and concurrences in the judgement have more value than concurrences and less value than dissents because they often agree in part and disagree in part with the majority's decision.

Yet being able to label when separate opinions to measure an idea such as *judicial activism* can be difficult, since such a claim is dependent on the context of the claim, making it difficult to ascribe certain words with *judicial activism*. I show how Large Language Models (LLMs) help overcome the concern of context, by labeling 190 separate opinions for the presence of *judicial activism* arguments at the sentence-level. Researchers often use bag-of-words approaches for text classification (Ballingrud 2021; Budziak, Hitt, and Lempert 2019; P. C. Corley, Steigerwalt, and Ward

[1] See (Bowden 2018; Carney 2022)
[2] See (Vargas 2022)

2023; Hazelton and Hinkle 2022; Owens and Wedeking 2011) which uses a select set of words to classify the presence of some important concept by placing a fixed value on each word. Yet LLMs do not assume the value of a word is fixed, allowing for nuanced relationships between words and when they are used, increasing performance in text classification tasks (J. Howard and Ruder 2018) Available resources limit the number of opinions I currently use for fine-tuning giving me, yet I label 190 opinions at the sentence and paragraph levels. Despite the low number of documents, I achieve classification performance comparable to other classification attempts on complex topics in legal documents (Ahmad, Harris, and Sahibzada 2020; H. Chen et al. 2022). I then fine-tune LEGAL-BERT (Chalkidis et al. 2020), a LLM trained on legal documents, to classify when 6,925 separate opinions from 1946 to 2014 make claims of *judicial activism*. Using a two-stage process to understand when Justices allege *judicial activism*, I adjust for possible selection bias when Justices decide to write separate opinions. My results suggest that Justices criticize the majority coalition of *judicial activism* most often in dissents Mixed results suggest justices who write dissents allege *judicial activism* based on the distance from the majority coalition, while disregarding the likelihood of media coverage. I also find mixed results suggesting that concurrences in the judgement view potential media coverage as a stronger cost when deciding to allege *judicial activism*.

This paper provides one of the first systematic looks into why Justices use arguments unique to separate opinions. Prior research examines both majority opinions and separate opinions make appeals to legal authorities (P. C. Corley, Howard, and Nixon 2005; Gates and Phelps 1996; R. M. Howard and Segal 2002, 2004; Hume 2006; Phelps and Gates 1990–1991), but either focus on specific citations, or hand code a limited number of opinions. By looking at *judicial activism*, the contribution of this paper is to show that Justices are motivated to write separate options with certain arguments in mind. By looking at substantive features of separate opinions, future research can investigate the effectiveness of these arguments on later interpretation of precedent by lower courts, and by the Supreme Court. Understanding the substance of these opinions is important to understand how future Justices use these opinions in judicial decision-making. This research opens multiple avenues of future research, such as looking at alternative arguments, or looking at differences in motivations across opinion types. The measurement strategy used in the paper also opens up future work on the substantive features and arguments found in any opinions. Understanding the substantive features of precedent can provide a more nuanced understanding of legal development, leading to a better understanding of how justices shape law through their writing.

Judicial Restraint and Judicial Activism

At its core *judicial restraint* is a judging norm through which Justices are expected to decide cases in a narrow manner, focusing on changing law as little as possible. *Judicial restraint* emphasizes "expanding the range of allowable judgement for legislatures, even if it means upholding conclusions they privately condemn" (Schlesinger, Jr. 1947). Strict interpretations on the constitution and the Supreme Court's role in government were further strengthened with the foundational article from Thayer (1893) saying "the judges must not interfere, since their question is a naked judicial one," signaling that justices are expected to defer to the legislative and executive branches when it comes to making policy. In this manner, Justices are expected to act in accordance with *judicial restraint* because they are not elected officials, and should thus decide law in a neutral manner, not according to personal policy preferences. *Judicial restraint* existed as an idea since the early days of the United States, with Thomas Jefferson being an advocate of the principle. The practice further became enmeshed with the expected way the Supreme Court ruled on cases, with Justice Brandeis even writing a set of guidelines in his concurrence of *Ashwander v. Tennessee Valley Authority* now known as the "Ashwander Rules" (Louis Brandeis 1936). These events set in stone the expectation that justices should practice *judicial restraint* by following *stare decisis*, issuing rulings on narrow grounds, only answering relevant questions in a case, and respecting the policies made by the executive and legislative branches of government. As a result, the norm of *judicial restraint* became a foundational aspect of the court, and those who deviated from it were labeled as engaging in *judicial activism*.

Judicial activism is a broad criticism a Justice makes when another Justice violates the norm of *judicial restraint*. The term was first connected to the idea that "[Judicial activism] is more concerned with the employment of the judicial power for their own conception of the social good" (Schlesinger, Jr. 1947). The negative connotation of *judicial activism* spread past the court system, with the public and elected officials holding negative views of *judicial activism*.[3] By alleging *judicial activism* in a separate opinion, concurring and dissenting Justices aim to decrease the validity of that decision in the eyes of the lower courts. *Judicial activism* thus signals the majority coalition is using their own views of prior precedent, supplementing their own beliefs for law, not deferring to elected officials, or deciding cases in a broad manner. This is a strong allegation, since it suggests the Supreme Court is deviating from how Justices are expected to rule on cases. While it is a strong allegation, it comes with heavy costs since using this kind of allegation too much would result in *judicial activism* losing its power to persuade the other audiences of the court. Given the expectations that come with making such an allegation, when can we expect Justices to make this argument in separate opinions?

Why Allege Judicial Activism?

I extend current theories of why Justices write separate opinions, and theorize that Justices decide to allege *judicial activism* as a function of the value they receive if they successfully persuade implementors, and likelihood that the public will hear about these allegations. Prior research suggests many factors influence a justice to write separate opinions including; ideological incompatibility, aspects of the collegial game such as prior cooperation, being the chief justice, or being a new justice on the court, the salience of a case, the complexity of the case, and the workload the Justices have in that term (Epstein, Landes, and Posner 2011; Wahlbeck, Spriggs, and Maltzman 1999). While Justices make many considerations when deciding to write a separate opinion, the same considerations do not play a role when deciding whether to make arguments about *judicial activism*. Borrowing from Black and Boyd (2013), I expect that Justices view the arguments they make in separate opinions as informational cues for decision implementors, and personally assign arguments they can make as being high or low cost, and high or low information. Justices hope

[3] See (Bowden 2018; Carney 2022; or Vargas 2022) for recent examples of *judicial activism* in the media.

to include as many high information costs in their separate opinions to effectively persuade decision implementors, while also avoiding the costs that come with some types of arguments. In this framework, I theorize that justices view *judicial activism* as a high information cue that signals the majority coalition is not following the traditions of the court.

The value of alleging *judicial activism* comes from how much law would change in favor of said justice's preferences if policy implementors are persuaded. Prior work finds ideology is a strong motivator for Justices seeking policy goals (Baum 2008; Segal and Spaeth 2002; Wahlbeck, Spriggs, and Maltzman 1999). I expect that the same applies here, with justices placing higher value on cases far from their personal preferences. This suggests that as decision outcomes get further from the preferences of a justice the more beneficial it is for that justice to claim *judicial activism*.

Despite the high information value of this argument, *judicial activism* can come with high costs. Justices do not want the public to notice when these allegations are made given the public's negative connotation of *judicial activism*. Justices rely on diffuse support for the court to enforce their decisions (Gibson and Nelson 2014), and allegations of *judicial activism* could threaten this support that the Supreme Court enjoys. As such I expect that when justices anticipate a case will be covered by the media, the cost of alleging *judicial activism* increases. While justices do not use different linguistic features in salient cases (Goelzhauser and Cann 2014; Owens and Wedeking 2011), I expect the types of arguments present in these opinions will change. Justices will use arguments with lower costs than *judicial activism*, to persuade both decision implementors and maintain diffuse support.

Justice's assign higher costs to *judicial activism* allegations when writing a concurring opinion or a concurrence in the judgement when compared to a dissenting opinion. Justices who write concurrences in the judgement often agree with the Court's disposition, but not with the reasoning the majority opinion puts forth. While justices who write concurrences agree with both the disposition and reasoning of a decision, often adding further justification or reasoning to the decision. This suggests that concurrences would not find value in alleging *judicial activism*, since policy is already close to their personal preferences. However, justices writing concurrences in the judgement could find value in alleging *judicial activism*, since they do not fully agree with the majority opinion's decision. Thus, I expect concurrences in the judgement to place value in making allegations of *judicial activism* ascribing said arguments with the same costs and values as those who write dissenting opinions. Justices writing concurrences often do so to support the decision of the majority, often by expanding on issues in a case or the precedent used to reach a decision. Because these justices already support the decision and justification of the majority, justices writing concurrences would not find value in accusing the majority of *judicial activism*. Justices who write concurrences on the judgement place a higher value in alleging *judicial activism* than those who write concurrences. This is because justices who write concurrences in the judgement often disagree with the rationale.

Data

My dependent variable in test my theory is the probability that each opinion is activist using the text of separate opinions as used by Rice (2017) and Sim, Routledge, and Smith (2014). This data contains 6,925 separate opinions from 1946 to 2014. The probability is the calculated by creating a binary variable for each paragraph indicating whether it contains *judicial activism*. I then take the sum of those binary indicators and divide by the number of paragraphs in the opinion, resulting in a variable ranging from 0 to 1 where 1 indicates every paragraph in an opinion was labeled as *judicial activism*. I also include a weighted version of this variable by weighting each paragraph based on the proportion of word in a paragraph in relation to the total number of words found in the opinion. The binary indicators are generated using Large Language model fine-tuned for this classification task, which I describe in detail in the next section.

I use the Supreme Court Database's justice-centered dataset to form my unit of analysis at the justice-case level (Spaeth et al. 2021). This provides me with justice-level votes for each case, including whether they joined or authored the majority or a separate opinion. The measures of *judicial activism* detailed above are merged in for authors and coauthors of opinions. In the event a Justice joins a separate opinion, but does not author or coauthor the opinion, they are assigned the same measure of *judicial activism* as the Justice they joined with. I then exclude remove from each case any Justice who either did not participate in the case or wrote the majority opinion. After these operations I have a dataset with 53,743 observations over 6,933 cases at the justice-case level spanning from 1945 to 2014.

I use preexisting measures to create the independent variables to measure ideological preference, and the likelihood that a case gains media coverage. Ideological preference is measured as the distance between the separate opinion writer and the ideological median of the majority decision. The ideological median of majority is shown to have the greatest influence over opinion location (Carrubba et al. 2012). But I also estimate the ideological preference as the distance between a Justice and the majority opinion author as a robustness check, since research has shown the author of the majority opinion to have a strong influence on the opinion content (Jeffrey R. Lax and Rader 2015). This ideological distance is estimated using the Martin-Quinn ideal points, which places Justices on a one-dimensional ideological space (Martin and Quinn 2002). I make this an absolute distance from the separate opinion writer and the majority coalition writer, consistent with prior works (Carrubba et al. 2012; Rice 2017). Ideology may also have a non-linear effect, where Justices see exponentially greater value the further away they are from the majority. As such I also square my measures of ideological preference and include them as a variable. I use the measure of early issue salience from Clark, Lax, and Rice (2015) as my indicator of the likelihood that a case gains media coverage. This early issue salience variable measures the importance of a case prior to being decided, by using a latent variable model based on media coverage of a case prior to decision. By generating estimates of early issue salience, this latent variable approach removing possible post-treatment bias that comes from measuring front-page stories in the New York Times the day after a decision (Epstein and Segal 2000). As the early issue salience of a case increase, the more likely it is that a case will receive media coverage post-decision.

I also control for a variety of variables that influence when a justice will write a separate opinion, including prior agreement between Justices, legal complexity, case-level characteristics, and justice-level characteristics.[4] Case complexity is controlled for using the case complexity measure generated by Goelzhauser, Kassow, and Rice (2021). This measure of case complexity uses the number of issues and provisions identified by the petitioner and respondent in merits briefs from 1957 to 2017 to generate latent complexity estimates. Greater values of case complexity here indicate a case is more complicated. Case complexity would likely decrease the value Justices have in writing alleging *judicial activism* by increasing the costs associated with making the claim. Justices writing separate opinions in complex cases contend with a complicated information environment, increasing the cost of a broad allegation like *judicial activism* and increasing the value found in making arguments against specific parts of a case.

I control for variation across issue areas using the Supreme Court Database's issue area coding (Spaeth et al. 2021). Different areas of law, such as civil rights cases, are more likely to have high issue salience, making it likely that justices will place higher values on changing policy in certain areas of law than others. I also distinguish the direction of a dissent, a binary variable indicating whether the dissenting opinion and the majority opinion both support or oppose the issue in a case. When the majority and the dissent are in the same direction there would be less value in alleging *judicial activism* because the resulting policy is already relatively close to their preferences. I also account for the personal salience of a case by using the scores generated by Black, Sorenson, and Johnson (2013) based on oral arguments. The authors use a standardized measure of how many words spoken by each justice in a case, where higher values indicate a case has a higher personal salience for that justice. Justices who find a case personally salience will place a higher value on ensuring policy on that issue is shaped according to their preferences, making this an important factor to control for. I also distinguish between the types of separate opinion a justice writes, and whether a justice authors or joins a separate opinion.

[4]These controls are detailed in the Appendix.

Measuring Judicial Activism

I use text-as-data methods to produce indicators of judicial activism in dissents. Past studies on Supreme Court opinions relied on bag-of-word approaches to generate measures (Black et al. 2016; P. Corley and Ward 2020; Rice 2017). These methods have limitations and remove context, not allowing for the measurement of more complex concepts (Grimmer and Stewart 2013). Large Language Models (LLMs) allow measurement on the context of a word, allowing for higher accuracy in measuring complex topics found in text. I use LEGAL-BERT (Chalkidis et al. 2020), an LLM trained on a corpus of legal documents coming from the US, UK, and EU, to measure when separate opinions contain *judicial activism* through fine-tuning the model on hand labeled opinions. Chalkidis et al. (2020) find that for tasks such as text-classification, generalized LLMs such as BERT or RoBERTa do not adapt well to legal documents. Legal documents often use very specialized vocabulary or grammar rules, making the legal domain a difficult area to use generalized dictionaries on.[5] The authors train a BERT (Devlin et al. 2018) style model using the same architecture as BERT with 12 layers, 768 hidden units, and 12 attention heads using a corpus of English legal text. They find that LEGAL-BERT performs better than BERT on tasks where legal domain knowledge is important, making this a suitable model for classifying allegations of *judicial activism*.

To measure *judicial activism*, seven undergraduate students and I labeled a randomly sampled set of separate opinions (N = 190). These labeled opinions span from 1946 to 2005. Coders were expected to label each sentence within the context of the whole opinion, giving them the necessary context of both the paragraph and opinion.[6] This gave me 10,312 sentence-level labels of which *judicial activism* shows up in 302 sentences. Of the 98 opinions that *judicial activism* shows up in, 31 are concurring opinions and 67 are dissenting opinions. Table 1 gives a detailed summary of the opinion labels at the sentence and paragraph levels.

[5] For example see how P. Corley and Ward (2020) discusses the difficulties of using pre-selected dictionaries for legal documents in footnote 3

[6] See Appendix for details on the coding of *judicial activism*, including the process, and codebook.

Table 1: Descriptive Statistics for Labels

	Sentence	Paragraph
Total Labels	10,312	2,550
Number of Judicial Activism	302 (2.93%)	235 (9.21%)
Opinions with Judicial Activism	98 (51.57%)	98 (51.57%)
Mean No. of Judicial Activism Mentions	1.589	1.237
Mean No. of Words per Opinion	1849	1849
Mean No. of Words per Judicial Activism mention	32.76	223.64
Mean Percentage Judicial Activism of Whole Opinion	7.89%	29.63%

Classifying with imbalanced data is difficult task, often resulting in machine-learning based approaches misclassifying rare events. While multiple remedies exist for alleviating issues in imbalanced data (Sun, Wong, and Kamel 2009), I fix this issue through undersampling the number of non-*judicial activism* labels in my training dataset. I undersample the training dataset by randomly selecting non-*judicial activism*, while keeping all *judicial activism* labels. This results in a dataset with 687 labeled sentences with approximately 35% (N = 207) of the labels being *judicial activism*. Training on a fully balanced dataset with 50% of the labels in each group proved to decrease the performance of the machine learning models, and increasing the proportion of non-*judicial activism* labels increased the performance of all models.

I trained both LEGAL-BERT and an XGBoost model on sentence and paragraph labels of *judicial activism* to form a comparison between traditional Bag of Words approaches and LLM classification. I separated the corpus of labeled sentences at the opinion level into training (N = 143) and validation (N = 47) sets, training each model on the training dataset and using the validation set to test the accuracy of the model. Training both models was done using the 2023 MacBook Pro with an M2 Pro chip and 16 GB of RAM. I fine-tuned LEGAL-BERT over four epochs, or four complete passes over the fine-tuning dataset, using the default hyperparameters suggested. XGBoost was trained using the default parameters, setting the maximum delta step to 4, and setting an early stopping point if the model did not improve the F1 score after 30 rounds.

Labels were also aggregated to the paragraph-level to gain more context around claims of *judicial activism*.[7] While it may be difficult to pick out a sentence that clearly makes a claim of *judicial activism*, it is easier to find allegations of *judicial activism* at a paragraph-level. Justices may spend a whole paragraph leading up to an allegation, making the whole paragraph important to understand the claim. LLMs can also take advantage of the additional context from paragraphs in classification. Thus, I also assess the performance of classification at the paragraph-level by aggregating the labels up to the paragraph-level. Paragraphs were labeled as *judicial activism* if any of the sentences within that paragraph was labeled as *judicial activism*.

To assess the performance of the classification model, I use four frequently used calculations, the F1 score, the precision score, the recall score, and the score of overall accuracy. The precision score measures the proportion of predictions correctly over all the labels classified in that category. The recall score measures the proportion of correctly labeled predictions over the total number of actual predictions in that category. And the F1 score is a mean of both the precision and recall. In the context of this classification, a high precision rate will mean fewer labels are incorrectly identified as *judicial activism*. A high recall score would mean that more labels identified as *judicial activism* are correctly identified as such by the classifier. For classifying a rare label such as *judicial activism* it is important to include these performance measures instead of only relying on accuracy. For example, if a 90% of labeled documents are in category "A", with the other 10% in category "B", an accuracy of 90% could signify the classification model labels all documents as "A". I place higher weight on the precision, recall, and F1 scores when validating the LEGAL-BERT and other models. Table 2 compares the performance of fine-tuned LEGAL-BERT in classifying paragraphs and documents against a bag-of-words approach. Classifying whole opinions was done using LEGAL-BERT trained on paragraphs, and a document was labeled as containing *judicial activism* if any paragraph in the document was classified as containing *judicial activism*.

[7] See Appendix for the current accuracy rates at the sentence-level.

Table 2: Performance Measures for Classification Model (With Thresholds)

Classification Level	Overall Accuracy	Precision	Recall	F1
LEGAL-BERT Paragraph	88.83%	0.80	0.46	0.58
LEGAL-BERT Paragraph (0.84)	90.74%	0.51	0.75	0.61
XGBoost Paragraph	82.49%	0.43	0.26	0.32
LEGAL-BERT Doc.	74.47%	1	0.64	0.78
LEGAL-BERT Doc. (0.974)	89.36%	0.83	0.95	0.89
XGBoost Doc.	55.32%	0.8571	0.5	0.63
XGBoost Doc. (0.84)	68.09%	0.8571	0.6	0.71

The performance measures here show the difficulty in classifying a rare and complex label, and the strengths of using an LLM in such a task. In all instances LEGAL-BERT performs better than XGBoost in classification at the paragraph and document levels, suggesting that context is important for measuring *judicial activism*. Despite the performance increases found in LEGAL-BERT, the measures of precision and recall at the paragraph level are less than ideal, with roughly half of all paragraphs labeled as *judicial activism* being a false positive. The performance of the document-level validation of LEGAL-BERT is much better though, with a precision of 0.83 and a recall of 0.95.

To avoid introducing a number of false positives into a binary indicator of an opinion containing a *judicial activism* allegation, I use LEGAL-BERT to generate a class probability. This class probability is the probability that a given opinion makes the judicial activism critique. I generate this class probability measure by classifying each paragraph using the LEGAL-BERT model into either containing *judicial activism* or not. I then take the mean value of all the paragraphs in an opinion, giving me a value between 0 and 1, with higher values indicating a higher probability that an opinion contains allegations of *judicial activism*. Introducing this class probability requires the assumption that the measurement error in the probability measure is not associated with any explanatory variables in used in the mode (Enamorado, Fifield, and Imai 2019). While there appear to be a number of false positives and false negatives in the data, I do believe these can be attributed to noise in the classification method. Fine-tuned Large Language Models frequently require a larger number of labels to achieve more accurate results in classification. Given the random selection of hand-coded labels, and a close inspection of the false positive and false negative texts, I believe the measurement error in the class probability can be attributed to noise.[8] The noise in the class probability thus should not bias the results of the regression models.

Research Design

I test my theoretical expectations using a two-stage selection model (Heckman 1976) modeling both when Justices write separate opinions, and then the probability that a separate opinion is classified as *judicial activism*. This is done to help correct for selection bias in the Justices who decide to write separate opinions. I first model the likelihood that a justice will write a separate opinion by including all the measures prior work has found to influence the decision to write a separate opinion using a probit function.[9] This model includes all justices who did not write the majority opinion, and excludes all justices who did not participate in a case. Given the probit function, I then calculate the inverse Mill's ratio to add into the second regression. The inverse Mill's ratio is then added to the second regression to control for selection bias in Justices who decide to write separate opinions.

The second stage of the model is an OLS regression, where I regress the probability a separate opinion contains *judicial activism* on the key independendent variables, and include the controls previously described. I first run a model with the inclusion of two dummy variables indicating if a justice wrote a concurrence in the judgement or a dissent. This model is run to understand if justices are more likely to mention *judicial activism* in one type of separate opinion or another. I then run individual models for each type of separate opinion to understand if justices make different considerations when writing different types of separate opinions. Table 3 presents models

[8]See the Appendix for an in-depth look on the opinions labeled as false positives and false negatives.

[9]An overview of the probit models and the controls used are discussed in the Appendix.

on separate opinions as a whole, and Table 4 presents the models on the three types of separate opinions. In addition, for all models I run two variations, one with the personal salience measure included, and one with the personal salience measure excluded, but with justice level fixed effects. This is because measures of personal salience only cover from 2004-2010, excluding a large amount of the data. I control for variation between different issue areas by using issue area fixed effects on all models. All models presented in Table 3 and Table 4 include justices who either wrote or joined onto a separate opinion. I include robustness checks in the Appendix where I subset down to justices who authored an opinion, and use the distance to the majority opinion author writer as an alternative measure of ideological preference.

Results

In Table 3 I find mixed support for my theory. I find that dissenting opinions are more likely to contain allegations of *judicial activism* against the majority opinion, although the increase is small at anywhere between 1.2% and 4% more likely than concurring opinions. Concurrences in the judgement show a surprising result in Model 2 and 4 where concurrences in the judgement are 2.8% less likely to contain an allegation of *judicial activism* when compared to concurring opinions. However, the result is mixed with robustness checks showing opposite effects. I am thus not confident in saying that *judicial activism* claims are no more likely to appear in concurrences in the judgement when compared to concurrences. Case complexity also exhibits a negative effect on the probability of *judicial activism* allegations appearing in a separate opinion. This suggests that justices view case complexity as a cost against making *judicial activism* claims. Additionally, I find limited support that issue salience decreases the likelihood a separate opinion includes *judicial activism* claims. Robustness checks also show a similar effect with issue salience, but the effect size and significance varies on the model.

The most interesting results in Table 3 come from ideological preferences. The results and robustness checks suggest that distance from the majority coalition increases the likelihood a justice will make an allegation of *judicial activism*, but the nature of this relationship is mixed. Models 1

Table 3: Change in Probability of Separate Opinion Containing Judicial Activism Claim

	Model 1	Model 2	Model 3	Model 4
Ideological Dist. (Median)	**−0.043***	**0.011***	**−0.064***	**0.015***
	(0.020)	(0.003)	(0.027)	(0.005)
Dist., Sq. (Median)	**0.008***	−0.001	**0.012***	−0.001
	(0.003)	(0.000)	(0.004)	(0.001)
Issue Salience	−0.003	**−0.007***	−0.002	**−0.013***
	(0.009)	(0.002)	(0.012)	(0.003)
Personal Salience	0.011		0.016	
	(0.007)		(0.010)	
Case Complexity	−0.017	**−0.009***	−0.009	**−0.012***
	(0.011)	(0.002)	(0.015)	(0.003)
Wrote Concurrence in Jud.	0.002	**−0.028***	−0.027	**−0.045***
	(0.027)	(0.005)	(0.037)	(0.008)
Wrote Dissent	**0.040***	**0.012***	0.039	**0.016***
	(0.015)	(0.003)	(0.021)	(0.005)
Justice Fixed Effects	No	Yes	No	Yes
Issue Area Fixed Effects	Yes	Yes	Yes	Yes
R^2	0.070	0.058	0.077	0.053
Adj. R^2	0.042	0.053	0.049	0.048
Num. obs.	572	9632	572	9629

Models 1 and 2 use the non-weighted probability while Models 3 and 4 use the weighted probability.

Table 4: Change in Probability in Types of Separate Opinion Containing Judicial Activism Claim

	Concur		Concur on Judgement		Dissent	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Ideological Dist. (Median)	−0.087	0.005	−0.077	−0.002	**−0.067***	0.005
	(0.045)	(0.009)	(0.074)	(0.008)	(0.028)	(0.004)
Dist., Sq. (Median)	0.015	0.001	0.027	0.001	**0.011***	0.000
	(0.010)	(0.002)	(0.016)	(0.001)	(0.004)	(0.001)
Issue Salience	0.032	0.002	−0.007	**−0.018***	0.004	−0.000
	(0.042)	(0.012)	(0.036)	(0.006)	(0.010)	(0.003)
Personal Salience	0.004		0.029		0.016	
	(0.012)		(0.030)		(0.009)	
Case Complexity	−0.001	−0.011	−0.038	−0.010	−0.013	**−0.009***
	(0.028)	(0.006)	(0.052)	(0.006)	(0.012)	(0.003)
Direction of Dissent					−0.185	−0.018
					(0.153)	(0.018)
Justice Fixed Effects	No	Yes	No	Yes	No	Yes
Issue Area Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.183	0.085	0.214	0.081	0.072	0.052
Adj. R^2	0.070	0.055	0.021	0.053	0.038	0.045
Num. obs.	116	1345	67	1538	389	6749

Table A6 in the Appendix shows the results using the weighted probabilities.

and 3 suggest that justices must meet a certain threshold distance from the majority to value alleging *judicial activism*, while Models 2 and 4 suggest a linear relationship. While the specific nature of the relationship is not known at this time, the results suggest that justices writing separate opinions are more willing to make allegations of *judicial activism* when they become distant from the majority coalition.

The results of Table 4 highlight heterogeneous effects, suggesting justices have different considerations when alleging *judicial activims* in a concurrence, a concurrence in the judgement, or a dissent. The results suggest two things, first that justices who write concurrences in the judgement pay attention to the issue salience of a case, and that dissenting justices make allegations of *judicial activism* after considering their personal preferences and the complexity of a case. For concurrences in the judgement, justices are less likely to allege *judicial activism* when a case is more salient, yet this effect has mixed significance. For Justices writing dissents, there is also mixed evidence to suggest that the ideological distance from the median justice plays a role in deciding when to make allegations of *judicial activism*. Altogether the results provide mixed results for my hypotheses of when justices decide to use *judicial activism* allegations in separate opinions.

Conclusion

I argued at the beginning of this article that justices treat arguments in separate opinions as informational cues for policy implementors, and assign arguments with costs and values that influence when they decide to use a specific argument. Here I focus on the argument of *judicial activism*, and hypothesize that justices find the argument valuable in persuading policy implementors, but the overall value of making *judicial activism* allegations is conditional on whether a case will be covered in the media, how much policy would change in favor of the justice, and the type of separate opinion a justice is writing. I measure the presence of *judicial activism* in separate opinions by using a fine-tuned Large Language Model, and provide mixed support for my hypotheses. By providing a framework of looking at the arguments in separate opinions as informational cues, and looking at the substance of the opinions, I help to understand what motivates Justices to make arguments in these opinions.

The findings that I have presented suggest that Justices have different motivations when deciding to allege *judicial activism*. Whether justices take into account their own preferences in relation to the majority coalition, the likelihood a case is covered by the media, or other aspects of a case, this work suggests that at justices who write dissents do so because they are motivated by policy preferences, consistent with prior literature (Baum 2008; P. Corley and Ward 2020; Wahlbeck, Spriggs, and Maltzman 1999). While research find dissents can influence the majority coalition (Rice 2017) and future legal development (Bryan and Ringsmuth 2016; P. C. Corley, Steigerwalt, and Ward 2023), little is known about how concurrences or concurrences in the judgement influence either the immediate or long-term legal development. Further exploring why justices decide to make certain arguments in separate opinions will help clarify what justices expect from writing these opinions, improving our understanding of separate opinion writing. Exploring the arguments in separate opinions can help clarify when these opinions reduce the clarity of a ruling (Westerland et al. 2010). Future work can also explore the heterogeneous effects this paper finds. For example, why would justices decide to make an argument in a concurrence in the judgement but not in a dissent? Future work on the concept of *judicial activism* can explore the effects opinions classified as *judicial activism* have on public opinion of the court, or on the future interpretation of decisions, testing the assumptions made in this paper.

This paper also contributes to the text-as-data methods used within judicial politics by providing an example of meaningful concepts that can be measured within the text of opinions. Research on Supreme Court opinions frequently focuses on keywords or features of dissents and concurrences, while this paper attempts to look at a substantive aspect of the opinions. By utilizing a Large Language Model, I show how measuring substantive content in opinions is now feasible. While this paper focuses on separate opinions, Large Language Models can help our understanding of majority opinions and legal development, such as the context in which justices cite certain precedent.

However, there is still difficulty in measuring an argument type such as *judicial activism*. The imbalanced ratio of *judicial activism* to non-*judicial activism* makes training a classifier such as LEGAL-BERT difficult without proper modifications. Future work could look at improving the classification of *judicial activism* through labeling more opinions. Despite the high performance of LEGAL-BERT at document-levels, further work could increase the number of labels of *judicial activism* at the sentence-and paragraph levels. Zheng and Jin (2020) finds machine learning methods perform the best at classify rare events when there is more data. Further, researchers have found a number of possible remedies for dealing with imbalanced data (Haixiang et al. 2017), providing a wide variety of alternative solutions to test and improve the classification of *judicial activism* at paragraph and sentence-levels.

References

Ahmad, Syed Rameel, Deborah Harris, and Ibrahim Sahibzada. 2020. "Understanding Legal Documents: Classification of Rhetorical Role of Sentences Using Deep Learning and Natural Language Processing." In *2020 IEEE 14th International Conference on Semantic Computing (ICSC)*, San Diego, CA, USA: IEEE, 464–67.

Ballingrud, Gordon. 2021. "Ideology and Risk Focus: Conservatism and Opinion-Writing In the U.S. Supreme Court." *Social Science Quarterly* 102(1): 281–300.

Baum, Lawrence. 1978. "Lower-Court Response to Supreme Court Decisions: Reconsidering a Negative Picture." *The Justice System Journal* 3(3): 208–19.

———. 2008. *Judges and their Audiences: A Perspective on Judicial Behavior*. Princeton, N.J. Oxford: Princeton University Press.

Black, Ryan C., and Christina L. Boyd. 2013. "Selecting the Select Few: The Discuss List and the U.S. Supreme Court's Agenda-Setting Process." *Social Science Quarterly* 94(4): 1124–44.

Black, Ryan C., Ryan J. Owens, Justin Wedeking, and Patrick C. Wohlfarth. 2016. *U.S. Supreme Court Opinions and their Audiences*. Cambridge: Cambridge University Press.

Black, Ryan C., Maron W. Sorenson, and Timothy R. Johnson. 2013. "Toward an Actor-Based Measure of Supreme Court Case Salience: Information-Seeking and Engagement During Oral Arguments." *Political Research Quarterly* 66(4): 804–18.

Black, Ryan C., and James F. Spriggs II. 2013. "The Citation and Depreciation of U.S. Supreme Court Precedent." *Journal of Empirical Legal Studies* 10(2): 325–58.

Bowden, John. 2018. "Trump Says He Will 'Reject Judicial Activism' When Picking Supreme Court Nominee." *The Hill*. https://thehill.com/homenews/administration/395791-trump-says-he-will-reject-judicial-activism-in-supreme-court-pick/.

Bryan, Amanda C., and Eve M. Ringsmuth. 2016. "Jeremiad or Weapon of Words?: The Power of Emotive Language in Supreme Court Dissents." *Journal of Law and Courts* 4(1): 159–85.

Budziak, Jeffrey, Matthew P. Hitt, and Daniel Lempert. 2019. "Determinants of Writing Style on the United States Circuit Courts of Appeals." *Journal of Law and Courts* 7(1): 1–28.

Carney, Jordain. 2022. "McConnell to Vote Against Jackson's Supreme Court Nomination." *The Hill*. https://thehill.com/homenews/senate/599663-mcconnell-to-vote-against-jacksons-supreme-court-nomination/.

Carrubba, Cliff, Barry Friedman, Andrew D. Martin, and Georg Vanberg. 2012. "Who Controls the Content of Supreme Court Opinions?" *American Journal of Political Science* 56(2): 400–412.

Chalkidis, Ilias et al. 2020. "LEGAL-BERT: The Muppets Straight Out of Law School."

Chen, Haihua et al. 2022. "A Comparative Study of Automated Legal Text Classification Using Random Forests and Deep Learning." *Information Processing & Management* 59(2): 102798.

Clark, Tom S., Jeffrey R. Lax, and Douglas Rice. 2015. "Measuring the Political Salience of Supreme Court Cases." *Journal of Law and Courts* 3(1): 37–65.

Corley, Pamela C., Robert M. Howard, and David C. Nixon. 2005. "The Supreme Court and Opinion Content: The Use of the Federalist Papers." *Political Research Quarterly* 58(2): 329.

Corley, Pamela C., Amy Steigerwalt, and Artemus Ward. 2023. *When Dissents Matter: Judicial Dialogue through US Supreme Court Opinions*. Charlottesville: University of Virginia Press.

Corley, Pamela, and Artemus Ward. 2020. "Intracourt Dialogue: The Impact of US Supreme Court Dissents." *Journal of Law and Courts* 8(1): 27–50.

Danelski, David J. 1967. "Conflict and Its Resolution in the Supreme Court." *Journal of Conflict Resolution* 11(1): 71–86.

Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. "BERT: Pre-Training of Deep Bidirectional Transformers for Language Understanding."

Enamorado, Ted, Benjamin Fifield, and Kosuke Imai. 2019. "Using a Probabilistic Model to Assist Merging of Large-Scale Administrative Records." *American Political Science Review* 113(2): 353–71.

Epstein, Lee, William M. Landes, and Richard A. Posner. 2011. "Why (And When) Judges Dissent: A Theoretical And Empirical Analysis." *Journal of Legal Analysis* 3(1): 101–37.

Epstein, Lee, and Jeffrey A. Segal. 2000. "Measuring Issue Salience." *American Journal of Political Science* 44(1): 66.

Gates, John B., and Glenn A. Phelps. 1996. "Intentionalism in Constitutional Opinions." *Political Research Quarterly* 49(2): 245–61.

Gibson, James L., and Michael J. Nelson. 2014. "The Legitimacy of the US Supreme Court: Conventional Wisdoms and Recent Challenges Thereto." *Annual Review of Law and Social Science* 10(1): 201–19.

Ginsburg, Ruth Bader. 2010. "The Role of Dissenting Opinions Lecture." *Minnesota Law Review* 95(1): 1–8. https://heinonline.org/HOL/P?h=hein.journals/mnlr95&i=1 (May 24, 2023).

Goelzhauser, Greg, and Damon M. Cann. 2014. "Judicial Independence and Opinion Clarity on State Supreme Courts." *State Politics & Policy Quarterly* 14(2): 123–41.

Goelzhauser, Greg, Benjamin J Kassow, and Douglas Rice. 2021. "Measuring Supreme Court Case Complexity." *The Journal of Law, Economics, and Organization* 38(1): 92–118.

Grimmer, Justin, and Brandon M. Stewart. 2013. "Text as Data: The Promise and Pitfalls of Automatic Content Analysis Methods for Political Texts." *Political Analysis* 21(3): 267–97.

Haixiang, Guo et al. 2017. "Learning from Class-Imbalanced Data: Review of Methods and Applications." *Expert Systems with Applications* 73: 220–39.

Hansford, Thomas G., and James F. Spriggs. 2018. *The Politics of Precedent on the U.S. Supreme Court*. Princeton University Press.

Hazelton, Morgan L. W., and Rachael K. Hinkle. 2022. *Persuading the Supreme Court: The Significance of Briefs in Judicial Decision-Making*. Lawrence, Kansas: University Press of Kansas.

Heckman, James J. 1976. "The Common Structure of Statistical Models of Truncation, Sample Selection and Limited Dependent Variables and a Simple Estimator for Such Models." In *Annals of Economic and Social Measurement, Volume 5, Number 4*, NBER, 475–92.

Hinkle, Rachael K., Andrew D. Martin, Jonathan David Shaub, and Emerson H. Tiller. 2012. "A Positive Theory And Empirical Analysis Of Strategic Word Choice In District Court Opinions." *Journal of Legal Analysis* 4(2): 407–44.

Hinkle, Rachael K., and Michael J. Nelson. 2017. "How to Lose Cases and Influence People." *Statistics, Politics and Policy* 8(2): 195–221.

Howard, Jeremy, and Sebastian Ruder. 2018. "Universal Language Model Fine-Tuning for Text Classification."

Howard, Robert M., and Jeffrey A. Segal. 2002. "An Original Look at Originalism." *Law & Society Review* 36(1): 113–38.

———. 2004. "A Preference for Deference? The Supreme Court and Judicial Review." *Political Research Quarterly* 57(1): 131–43.

Hume, Robert J. 2006. "The Use of Rhetorical Sources by the U.S. Supreme Court." *Law & Society Review* 40(4): 817–44.

Johnson, Charles A. 1979. "Lower Court Reactions to Supreme Court Decisions: A Quantitative Examination." *American Journal of Political Science* 23(4): 792–804.

———. 1987. "Law, Politics, and Judicial Decision Making: Lower Federal Court Uses of

Supreme Court Decisions." *Law & Society Review* 21(2): 325.

Lax, J. R., and C. M. Cameron. 2007. "Bargaining and Opinion Assignment on the US Supreme Court." *Journal of Law, Economics, and Organization* 23(2): 276–302.

Lax, Jeffrey R., and Kelly Rader. 2015. "Bargaining Power in the Supreme Court: Evidence from Opinion Assignment and Vote Switching." *The Journal of Politics* 77(3): 648–63.

Lindquist, Stefanie A., and Frank B. Cross. 2009. *Measuring Judicial Activism*. New York: Oxford Univ. Press.

Louis Brandeis. 1936. 297 U.S. (United States Supreme Court) *Ashwander v. Tennessee Valley Authority*.

Martin, Andrew D., and Kevin M. Quinn. 2002. "Dynamic Ideal Point Estimation via Markov Chain Monte Carlo for the U.S. Supreme Court, 1953–1999." *Political Analysis* 10(2): 134–53.

Nelson, Michael J., and Rachael K. Hinkle. 2018. "Crafting the Law: How Opinion Content Influences Legal Development." *Justice System Journal* 39(2): 97–122.

Owens, Ryan J., and Justin P. Wedeking. 2011. "Justices and Legal Clarity: Analyzing the Complexity of U.S. Supreme Court Opinions." *Law & Society Review* 45(4): 1027–61.

Phelps, Glenn A., and John B. Gates. 1990–1991. "The Myth of Jurisprudence: Interpretive Theory in the Constitutional Opinions of Justices Rehnquist and Brennan." *Santa Clara Law Review* 31: 567. https://heinonline.org/HOL/Page?handle=hein.journals/saclr31&id=585&div=&collection=.

Rice, Douglas R. 2017. "Issue Divisions and US Supreme Court Decision Making." *The Journal of Politics* 79(1): 210–22.

Scalia, Antonin. 1994. "The Dissenting Opinion." *Journal of Supreme Court History* 1994(1): 33–44. https://heinonline.org/HOL/P?h=hein.journals/jspcth1994&i=41 (May 24, 2023).

Schlesinger, Jr., Arthur M. 1947. "The Supreme Court: 1947." *Fortune* (January).

Segal, Jeffrey Allan, and Harold J. Spaeth. 2002. *The Supreme Court and the Attitudinal Model Revisited*. Cambridge, UK ; New York: Cambridge University Press.

Sim, Yanchuan, Bryan Routledge, and Noah A. Smith. 2014. "The Utility of Text: The Case of Amicus Briefs and the Supreme Court."

Spaeth, Harold J. et al. 2021. "Supreme Court Database, Version 2021 Release 1." http://supremecourtdatabase.org.

Spriggs, James F. 1996. "The Supreme Court and Federal Administrative Agencies: A Resource-Based Theory and Analysis of Judicial Impact." *American Journal of Political Science* 40(4): 1122–51.

Sun, Yanmin, Andrew K. C. Wong, and Mohamed S. Kamel. 2009. "Classification of Imbalanced Data: A Review." *International Journal of Pattern Recognition and Artificial Intelligence* 23(04): 687–719.

Thayer, James B. 1893. "The Origin and Scope of the American Doctrine of Constitutional Law." *Harvard Law Review* 7(3): 129.

Thomas Jefferson. 1825. "From Thomas Jefferson to Edward Livingston, 25 March 1825." https://founders.archives.gov/documents/Jefferson/98-01-02-5077.

Vargas, Ramon Antonio. 2022. "Kamala Harris Lashes Out at 'Activist' Supreme Court over Roe v Wade Decision." *The Guardian*. https://www.theguardian.com/us-news/2022/sep/09/kamala-harris-activist-supreme-court-roe-v-wade-abortion.

Wahlbeck, Paul J., James F. Spriggs, and Forrest Maltzman. 1999. "The Politics of Dissents and Concurrences on the U.S. Supreme Court." *American Politics Quarterly* 27(4): 488–514.

Wedeking, Justin. 2010. "Supreme Court Litigants and Strategic Framing." *American Journal of Political Science* 54(3): 617–31.

Westerland, Chad et al. 2010. "Strategic Defiance and Compliance in the U.S. Courts of Appeals." *American Journal of Political Science* 54(4): 891–905.

Zheng, Wanwan, and Mingzhe Jin. 2020. "The Effects of Class Imbalance and Training Data Size on Classifier Learning: An Empirical Study." *SN Computer Science* 1(2): 71.

Zink, James R., James F. Spriggs, and John T. Scott. 2009. "Courting the Public: The Influence of Decision Attributes on Individuals' Views of Court Opinions." *The Journal of Politics* 71(3): 909–25.

Appendix

Coding Rules

Seven undergraduate students assisted me in the hand-coding of these labels. Students were expected to label 80 opinions, yet only one student labeled that many opinions. The other undergraduate students labeled an average of 44 opinions. Each opinion was labeled by three coders, and I reviewed any disagreements in labels. Inter-coder agreement was an average of 61.54% over all the labels.

In addition, the coders were given the following rules as a guideline based on aspects of *judicial activism* highlighted in Lindquist and Cross (2009):

> Please label sentences using the following guidelines:
>
> Institutional Activism: - Diversions from precedent - When a justice accuses the majority coalition of diverting from prior decisions made by the Supreme Court.
>
> - Striking down constitutional acts from the legislature or executive.
>   - When a justice accuses the majority coalition of restricting law or policies that should be considered constitutional.
> - Diversions from conventional interpretations
>   - When a justice accuses the majority coalition of not following how prior courts have interpreted words, phrases, or tests.
> - Legislating from the bench
>   - When the justice accuses the majority coalition of creating new laws when they should be interpreting existing law.
>
> Ideological Activism: - Ruling based on preferences and not on rules. - When the justice accuses the majority coalition of not interpreting law based on prior rulings or laws, but rather by their own beliefs.
>
> Notes:
>
> - If Justices allege any of these things but state them as their personal opinion, do not label as either "ideological" or "institutional".
>   - e.g. "I am not convinced this reading of the U.S.-CONST.-AMEND.-5 is correct, but need not rely on a different interpretation here. and the 483-U.S.-435 Court has held this exception applicable to the U.S.-CONST.-AMEND.-6 right to trial by jury as well."

There may be concerns due to the subjectiveness found in these categories. Legal scholarship finds *judicial activism* to be a difficult task to accurately define, with many works trying to make sense of the term (Green 2009; Kmiec 2004; Lindquist and Cross 2009). By basing my codebook off of the areas of *judicial activism* as defined by Lindquist and Cross (2009), I hope to provide a foundation on which further research can explore alternative classifications of *judicial activism*.

Table A1: Confusion Matrix for fine-tuned LEGAL-BERT with thresholds

	Predicted (Paragraph)	
Actual Values	Not Activism	Activism
Not Activism	658	54
Activism	19	57

	Predicted (Document)	
Actual Values	Not Activism	Activism
Not Activism	22	4
Activism	1	20

Examining False Positives

Table A1 shows the confusion matrices for the validation of LEGAL-BERT at the paragraph and document levels with the 0.84 and 0.974 thresholds respectively. At the document-level there are four cases that exhibit false positives. They are Justice Douglas's dissent in *Pugach v. Dollinger*, Justice Marshall's dissent in *Davis v. United States* (1973), Justice White's concurrence in *Ylst v. Nunnemaker*, and Justice O'Connor's concurrence in *Garrett v. United States*. There is also one false negative with Justice Brennan's concurrence in *United States v. Mersky* (1960). I first discuss whether each opinion should be classified as a false positive or negative, and then discuss the implications with these incorrectly identified opinions. I then discuss the presence of false positives at the paragraph level, and the implications this misclassification has when labeling at the paragraph level.

In Justice Douglas's dissent, he discusses how "a majority of this Court summarily holds that [*Schwartz v. Texas*] is still the law," in a case concerning wiretapping. Justice Douglas suggests that the majority ignored the current precedent of *Benanti v. United States* a case distinguishing the precedent set forth in *Schwartz v. Texas*. Under the current codebook for *judicial activism*, this would fall under the classification of "diverting from precedent" and is thus correctly identified as *judicial activism*. For Justice Marshall's dissent in *Davis v. United States*, he states "I am not persuaded by that argument, and find the majority opinion clearly defective." suggesting this is his personal opinion on the law. Since he is not making an accusation against the court, and only stating his opinion, this opinion is falsely labeled as *judicial activism* Justice White's concurrence in *Ylst v. Nunnemaker* is incorrectly labeled as *judicial activism* because Justice White writes to make clear he assumes the majority opinion does not attempt to restrict a presumption based on a quotation used. Justice O'Connor's concurrence in *Garrett v. United States* is written to discuss at length why "[*Garrett v. United States*]'s holding comports with the fundamental purpose of the Double Jeopardy Clause and with the method of analysis used in our more recent decisions." Thus, this opinion is also falsely identified as *judicial activism*.

Justice Brennan's concurrence in *United States v. Mersky* (1960) labeling as a false negative appear to be a correct labeling. Justice Brennan wrote this concurrence in response to "arguments are made [in the] dissent which would unsettle what has been settled by our precedents and reintroduce archaisms into federal criminal procedure." The paragraphs incorrectly labeled as *judicial activism* in the dataset discuss how the dissenting opinion written by Justice Frankfurter, Justice Harlan, and Justice Stewart would ignore prior precedent. In this then Justice Brennan is accusing the dissenting opinion writers of disregarding judicial norms, not the majority opinion. As such the opinion is correctly identified as not containing *judicial activism* as defined by the scope of this paper. Future work however, could look at when instances such as this, where justices accuse those not in the majority of disregarding judicial norms.

The three opinions left, Justice Marshall's dissent in *Davis v. United States*, Justice White's concurrence in *Ylst v. Nunnemaker*, and Justice O'Connor's concurrence in *Garrett v. United States* are all incorrectly identified under the document-level classification structure of LEGAL-BERT. These three opinions do not appear to have any significant patterns of deviation from the variables of interest, issue salience, ideological preference, and the types of opinions these are present in. All three opinions fall within the first and third quantiles of issue salience, and ideological preference. In addition, while none of the opinions are a concurrence in the judgement, there is not enough to say either dissents or concurrences are systematically misclassified.

At the paragraph-level there are 54 false-positive paragraphs, 34 of which come from documents with at least one other paragraph originally labeled as *judicial activism*. As such I disregard these paragraphs due to the presence of *judicial activism* already in these opinions. Of the remaining 20 false positive paragraphs, 10 are found in the opinions discussed above. The remaining 10 paragraphs are found in 3 concurrences, 2 concurrences in the judgement, and 3 dissents. Further examining these 10 paragraphs, they are all false positives. These 8 opinions also do not appear to be correlated with the key independent variables in any meaningful way. There is one possible concern with Justice Douglas's concurrence in the judgement in *Lehman v. City of Shaker Heights* being labeled as activist. Justice Douglas's distance from the median in the majority coalition is the maximum distance of any justice writing a concurrence in the judgement with a value of 9.169. However, because all other opinions appear to be correlated with the independent variables, I view this concurrence in the judgement as an outlier.

Comparisons to Bag of Word Approaches

Bag-of-words comparisons were done using gradient boosted decision trees, specifically using the XGBoost package in Python (T. Chen and Guestrin 2016). Comparisons were done at the sentence-level and at the paragraph-level and thresholded at a point that adequately balanced for precision and recall. Table A2 presents classification metrics at the sentence-level. LEGAL-BERT was found to perform the best when trained over five epochs instead of the four epochs at the paragraph levels. All thresholds were performed in the same way, in trying to achieve the best balance between precision and recall. Notably, all versions of the classification models perform much worse than any of the models classifying at the paragraph level.

Table A2: Classification Metrics, Sentence Level

Classification Level	Overall Accuracy	Precision	Recall	F1
XGBoost	83.41%	0.38	0.08	0.14
XGBoost (0.821)	92.12%	0.22	0.13	0.16
LEGAL-BERT	85.47%	0.81	0.17	0.28
LEGAL-BERT (0.999)	95.12%	0.51	0.35	0.42

Alternative Specifications, LLMs

In addition to comparing performance across BERT, RoBERTa, and LEGAL-BERT, I also varied the proportion of non-*judicial actiivsm* labels in the case-control dataset. I found that with the current number of labelled instances of *judicial activism*, a proportion of any lower than 65% non-*judicial activism* labels significantly reduced the accuracy, recall, and precision of the LLMs across the board. I suspect this is due to the low number of *judicial activism* labels, making it difficult for the LLM to properly identify differences in paragraphs or sentences without enough variation. Future work can increase the number of labels to help achieve even higher measures of model performance at the paragraph and sentence-levels.

Figure A1: LLM Comparisons, Paragraph-Level

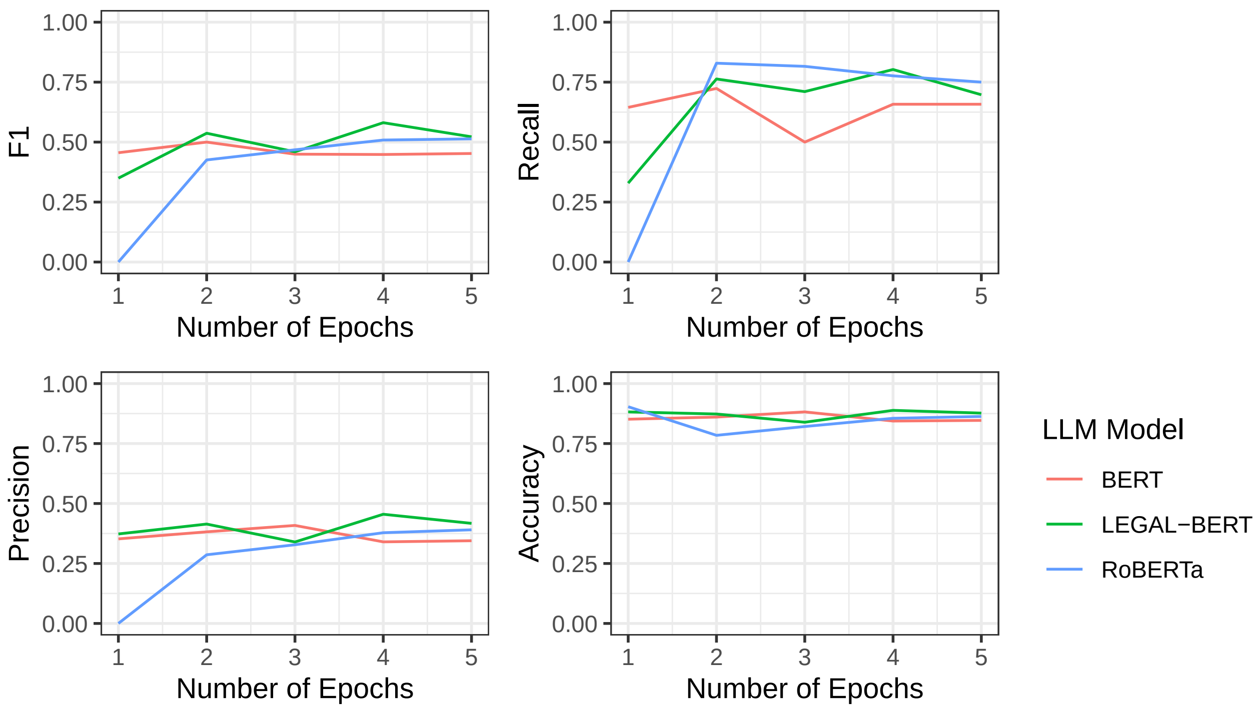
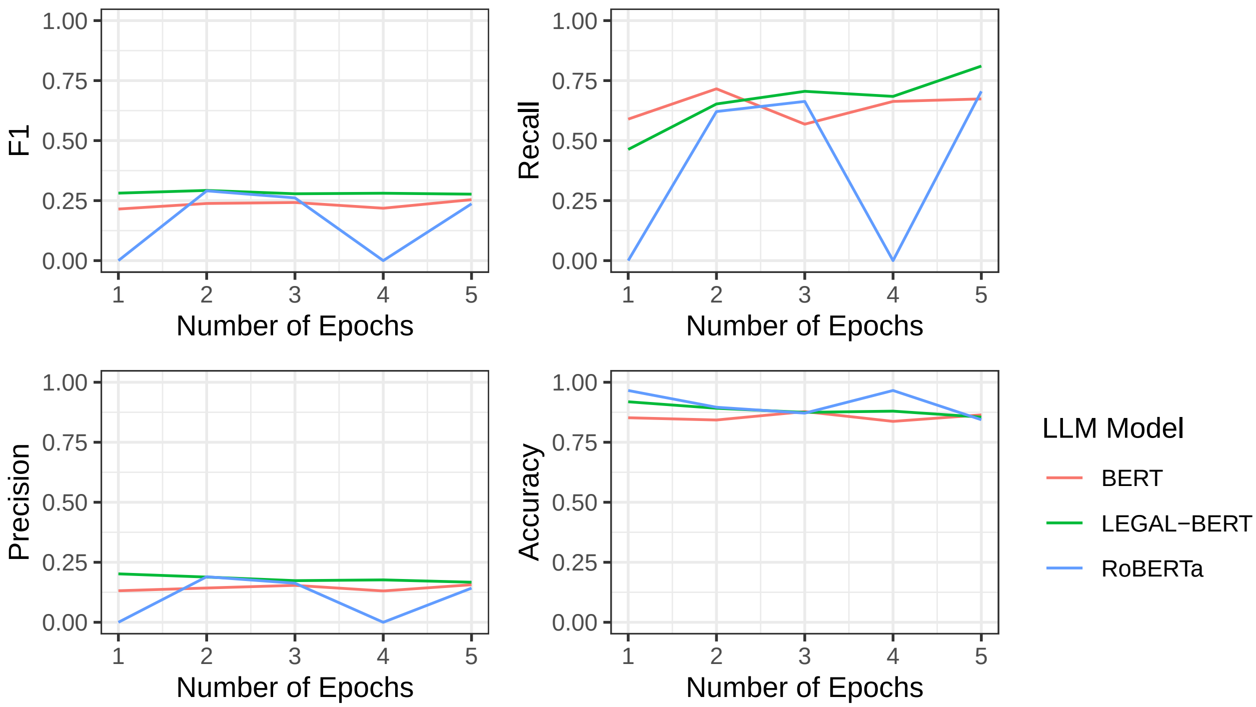


Figure A2: LLM Comparisons, Sentence-Level



Predicted Probability and Thresholds

Figure A3 shows the predicted probabilities of the paragraphs labeled in the validation set. Without any adjustment, anything below 0.50 would be classified as "Not Judicial Activism", while anything above is labeled as "Judicial Activism". One difficulty in labeling a rare task is the with how quickly the machine learning model ascribes extreme predicted probability values to paragraphs. After 4 epochs, the majority of paragraphs gain a predicted probability near 0 or near 1.

I separate out the false positives and true positives in Figure A4 to further show the difficulty in maintaining a high precision and recall when classifying rare events. Increasing the threshold in which a document is classified as the rare event can only increase the precision and recall if a higher threshold only removes false positives. In the 3 epoch LEGAL-BERT model, the higher number of paragraphs being categorized as *judicial activism* would result in a higher precision over time, since the number of false positives decreases in relation to the total number of labels classified as positive. However, true positives are also being excluded from the measure, reducing the recall over time. The 4 epoch LEGAL-BERT model encounters the same issue, but the low number of true positives below 0.9 means that the threshold can be increased to increase precision without a significant impact on the recall of the classifier. Yet once the threshold is increased past 0.9, the false positives and true positives become harder to distinguish from each other. Figure A5 and Figure A6 show these changes in the precision, recall, F1 and overall accuracy when adjusting the threshold in which a label is identified as *judicial activism* at 0.001 intervals, and how this aggregates up to the document level.

Figure A3: Predicted Probabilities of Labeled Paragraphs in Validation Set

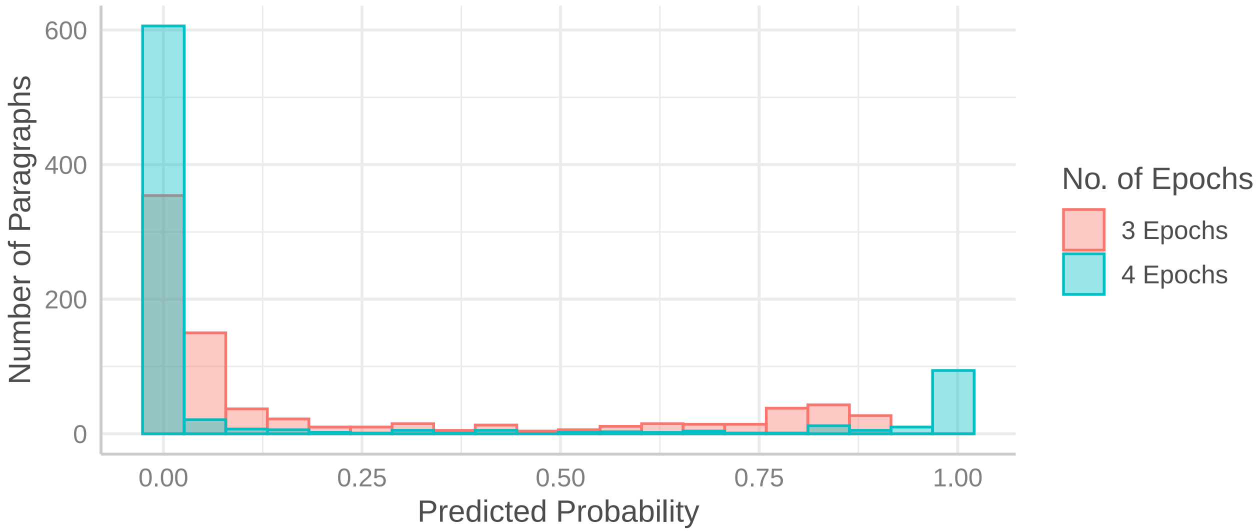


Figure A4: Predicted Probabilities of False Positives and True Positives

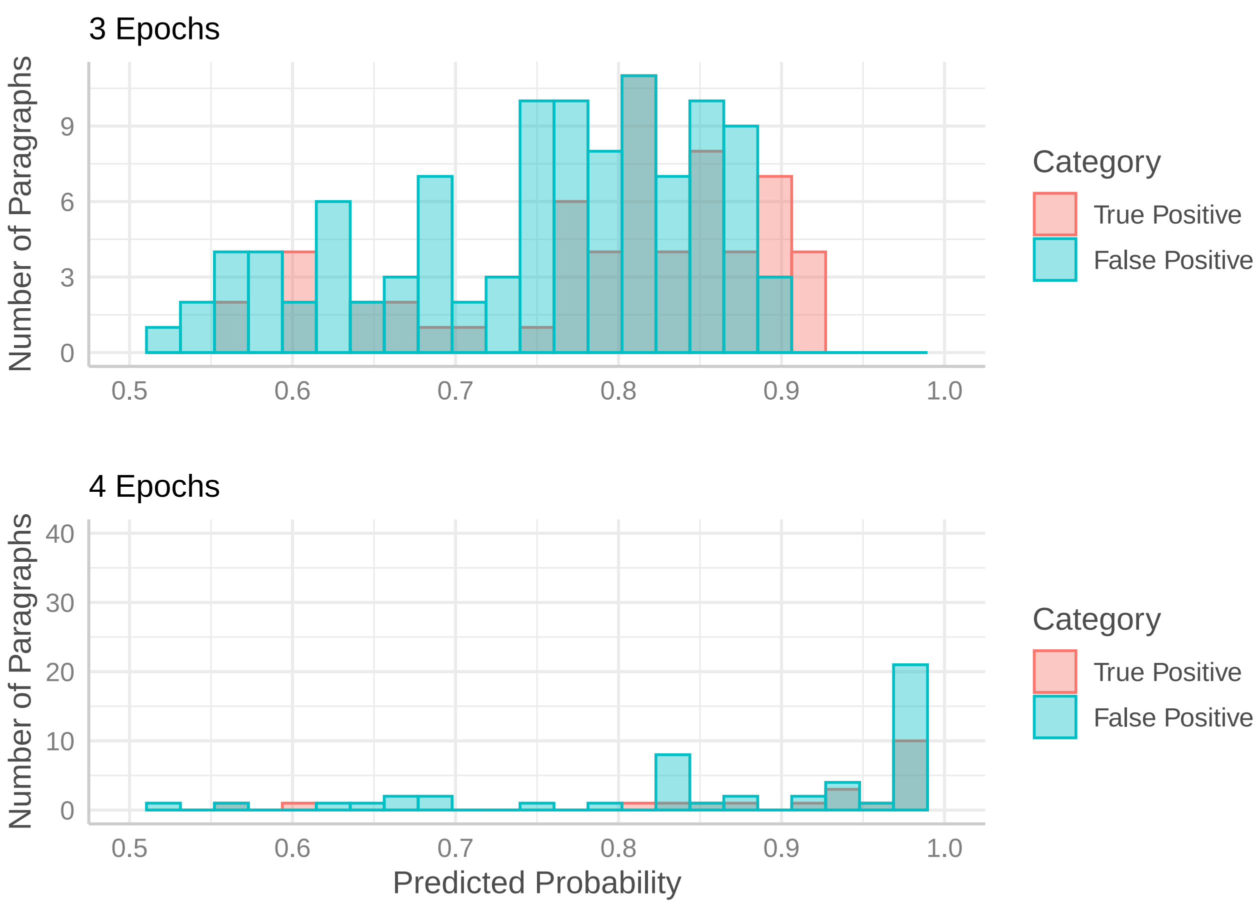


Figure A5: Classification Measures - LEGAL-BERT (Paragraph-Level)

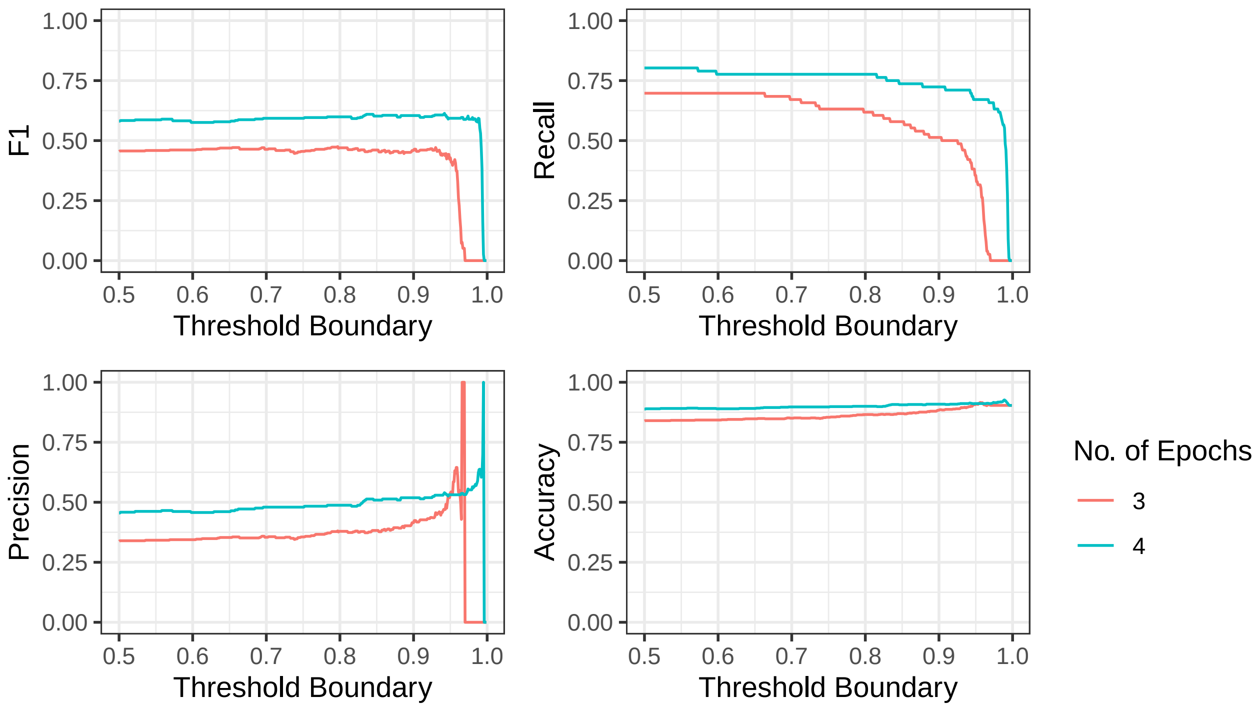


Figure A6: Classification Measures - LEGAL-BERT (Document-Level)

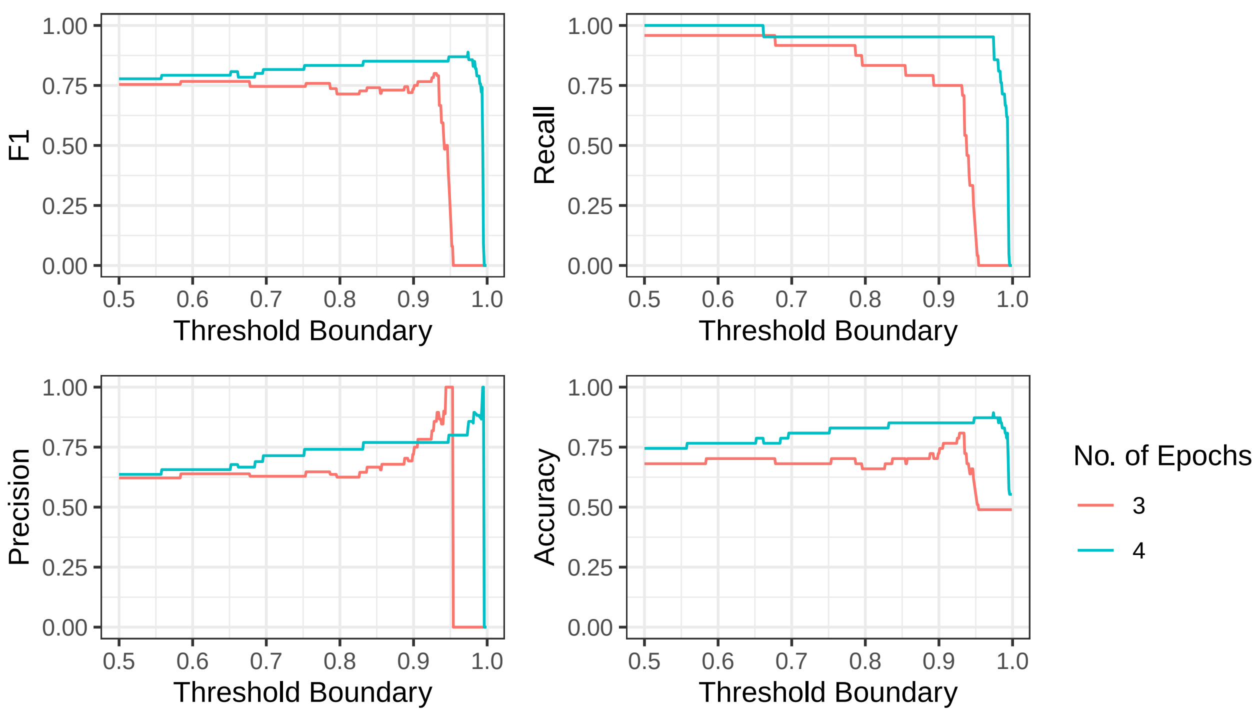


Table A3: Change in Probability of Separate Opinion Containing Judicial Activism Claim (Only Authors)

	Model 1	Model 2	Model 3	Model 4
Ideological Dist. (Median)	-0.040	$\mathbf{0.009}^{*}$	-0.067	0.007
	(0.029)	(0.004)	(0.038)	(0.006)
Dist., Sq. (Median)	0.009	-0.000	$\mathbf{0.015}^{*}$	0.000
	(0.005)	(0.001)	(0.006)	(0.001)
Issue Salience	0.000	-0.004	0.005	$\mathbf{-0.012}^{*}$
	(0.014)	(0.003)	(0.018)	(0.005)
Personal Salience	0.009		0.013	
	(0.012)		(0.016)	
Case Complexity	-0.028	-0.006	-0.012	-0.008
	(0.016)	(0.003)	(0.021)	(0.005)
Wrote Concurrence in Jud.	0.018	$\mathbf{0.018}^{*}$	-0.003	$\mathbf{0.025}^{*}$
	(0.035)	(0.006)	(0.046)	(0.010)
Wrote Dissent	$\mathbf{0.058}^{*}$	$\mathbf{0.069}^{*}$	0.068	$\mathbf{0.104}^{*}$
	(0.027)	(0.006)	(0.036)	(0.009)
Justice Fixed Effects	No	Yes	No	Yes
Issue Area Fixed Effects	Yes	Yes	Yes	Yes
R^2	0.085	0.099	0.102	0.098
Adj. R^2	0.030	0.091	0.048	0.089
Num. obs.	299	5113	299	5111

Models 1 and 2 use the non-weighted probability while Models 3 and 4 use the weighted probability.

Table A4: Change in Probability of Separate Opinion Containing Judicial Activism Claim (Only Authors)

	Model 1	Model 2	Model 3	Model 4
Ideological Dist. (Op. Writer)	−0.024	**0.010***	−0.030	**0.012***
	(0.025)	(0.003)	(0.033)	(0.004)
Dist., Sq. (Op. Writer)	0.004	**−0.001***	0.005	**−0.001***
	(0.003)	(0.000)	(0.005)	(0.001)
Issue Salience	−0.007	−0.006	−0.006	**−0.013***
	(0.015)	(0.004)	(0.020)	(0.005)
Personal Salience	0.008		0.010	
	(0.012)		(0.016)	
Case Complexity	−0.027	**−0.006***	−0.011	−0.009
	(0.016)	(0.003)	(0.021)	(0.005)
Wrote Concurrence in Jud.	0.020	**0.017***	−0.001	**0.024***
	(0.035)	(0.006)	(0.047)	(0.010)
Wrote Dissent	**0.065***	**0.073***	**0.079***	**0.108***
	(0.025)	(0.005)	(0.033)	(0.008)
Justice Fixed Effects	No	Yes	No	Yes
Issue Area Fixed Effects	Yes	Yes	Yes	Yes
R^2	0.078	0.099	0.085	0.098
Adj. R^2	0.022	0.091	0.030	0.089
Num. obs.	299	5113	299	5111

Models 1 and 2 use the non-weighted probability while Models 3 and 4 use the weighted probability.

Table A5: Change in Probability of Separate Opinion Containing Judicial Activism Claim

	Model 1	Model 2	Model 3	Model 4
Ideological Dist. (Op. Writer)	−0.001	**0.005***	0.004	**0.007***
	(0.016)	(0.002)	(0.022)	(0.003)
Dist., Sq. (Op. Writer)	0.000	**−0.001***	0.001	**−0.001***
	(0.002)	(0.000)	(0.003)	(0.000)
Issue Salience	−0.003	**−0.007***	−0.002	**−0.014***
	(0.010)	(0.002)	(0.013)	(0.003)
Personal Salience	0.010		0.015	
	(0.007)		(0.010)	
Case Complexity	−0.016	**−0.010***	−0.006	**−0.013***
	(0.011)	(0.002)	(0.015)	(0.003)
Wrote Concurrence in Jud.	−0.000	**−0.034***	−0.033	**−0.054***
	(0.027)	(0.005)	(0.037)	(0.008)
Wrote Dissent	**0.044***	**0.015***	**0.046***	**0.020***
	(0.015)	(0.003)	(0.021)	(0.005)
Justice Fixed Effects	No	Yes	No	Yes
Issue Area Fixed Effects	Yes	Yes	Yes	Yes
R^2	0.061	0.052	0.070	0.047
Adj. R^2	0.032	0.047	0.041	0.042
Num. obs.	572	9632	572	9629

Models 1 and 2 use the non-weighted probability while Models 3 and 4 use the weighted probability.

Table A6: Change in Weighted Probability in Types of Separate Opinion Containing Judicial Activism Claim

	Concur		Concur on Judgement		Dissent	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Ideological Dist. (Median)	−0.113	0.010	−0.095	−0.014	**−0.083***	0.007
	(0.069)	(0.014)	(0.085)	(0.012)	(0.038)	(0.006)
Dist., Sq. (Median)	0.020	0.000	0.030	0.002	**0.014***	0.000
	(0.015)	(0.003)	(0.018)	(0.002)	(0.006)	(0.001)
Issue Salience	0.060	0.001	−0.014	**−0.029***	0.006	−0.002
	(0.064)	(0.019)	(0.042)	(0.009)	(0.014)	(0.004)
Personal Salience	0.009		0.034		0.021	
	(0.019)		(0.035)		(0.013)	
Case Complexity	0.025	−0.018	−0.030	**−0.021***	−0.006	**−0.008***
	(0.043)	(0.010)	(0.060)	(0.009)	(0.016)	(0.004)
Direction of Dissent					−0.267	−0.032
					(0.206)	(0.026)
Justice Fixed Effects	No	Yes	No	Yes	No	Yes
Issue Area Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.218	0.070	0.269	0.083	0.065	0.047
Adj. R^2	0.110	0.040	0.090	0.055	0.030	0.041
Num. obs.	116	1345	67	1538	389	6746

$^{*}p < 0.05$

Table A7: Change in Probability in Types of Separate Opinion Containing Judicial Activism Claim (Only Authors)

	Concur		Concur on Judgement		Dissent	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Ideological Dist. (Median)	−0.098	−0.002	−0.102	0.001	−0.084	0.009
	(0.054)	(0.010)	(0.102)	(0.010)	(0.046)	(0.006)
Dist., Sq. (Median)	0.019	0.002	0.042	0.000	0.012	0.000
	(0.011)	(0.002)	(0.023)	(0.002)	(0.007)	(0.001)
Issue Salience	−0.015	−0.003	0.004	$-\mathbf{0.021}^{*}$	0.021	−0.002
	(0.048)	(0.013)	(0.048)	(0.008)	(0.017)	(0.004)
Personal Salience	0.010		0.094		0.009	
	(0.023)		(0.068)		(0.015)	
Case Complexity	−0.010	−0.005	−0.073	−0.004	−0.028	$-\mathbf{0.009}^{*}$
	(0.035)	(0.008)	(0.080)	(0.007)	(0.019)	(0.004)
Direction of Dissent					−0.223	−0.025
					(0.179)	(0.025)
Justice Fixed Effects	No	Yes	No	Yes	No	Yes
Issue Area Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.168	0.076	0.286	0.092	0.119	0.090
Adj. R^2	−0.017	0.034	−0.014	0.049	0.042	0.076
Num. obs.	78	961	45	1012	176	3123

$^{*}p < 0.05$

Table A8: Change in Probability in Types of Separate Opinion Containing Judicial Activism Claim (Only Authors)

	Concur		Concur on Judgement		Dissent	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Ideological Dist. (Op. Writer)	0.035	0.005	−0.147	0.003	−0.025	**0.014***
	(0.051)	(0.007)	(0.099)	(0.007)	(0.031)	(0.004)
Dist., Sq. (Op. Writer)	−0.006	−0.001	**0.026***	−0.001	0.002	**−0.001***
	(0.008)	(0.001)	(0.012)	(0.001)	(0.004)	(0.000)
Issue Salience	−0.015	−0.014	−0.027	**−0.020***	0.013	−0.003
	(0.048)	(0.012)	(0.051)	(0.008)	(0.016)	(0.004)
Personal Salience	−0.004		0.070		0.007	
	(0.023)		(0.063)		(0.015)	
Case Complexity	−0.001	−0.006	−0.075	−0.003	−0.028	**−0.009***
	(0.035)	(0.007)	(0.079)	(0.007)	(0.019)	(0.004)
Direction of Dissent					−0.200	−0.025
					(0.179)	(0.025)
Justice Fixed Effects	No	Yes	No	Yes	No	Yes
Issue Area Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.132	0.075	0.313	0.092	0.061	0.092
Adj. R^2	−0.061	0.033	0.025	0.050	0.022	0.078
Num. obs.	78	961	45	1012	176	3123

$^*p < 0.05$

Table A9: Change in Weighted Probability in Types of Separate Opinion Containing Judicial Activism Claim (Only Authors)

	Concur		Concur on Judgement		Dissent	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Ideological Dist. (Median)	−0.130	0.002	−0.147	−0.012	**−0.126***	0.009
	(0.086)	(0.016)	(0.117)	(0.015)	(0.058)	(0.008)
Dist., Sq. (Median)	0.026	0.002	0.051	0.002	**0.021***	0.001
	(0.017)	(0.003)	(0.027)	(0.003)	(0.009)	(0.001)
Issue Salience	−0.012	−0.011	0.007	**−0.030***	0.027	−0.006
	(0.076)	(0.021)	(0.055)	(0.012)	(0.021)	(0.006)
Personal Salience	0.030		0.105		0.005	
	(0.037)		(0.079)		(0.019)	
Case Complexity	0.008	−0.011	−0.076	−0.012	−0.012	−0.008
	(0.056)	(0.012)	(0.092)	(0.011)	(0.024)	(0.005)
Direction of Dissent					−0.290	−0.048
					(0.226)	(0.035)
Justice Fixed Effects	No	Yes	No	Yes	No	Yes
Issue Area Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.182	0.065	0.332	0.092	0.112	0.089
Adj. R^2	0.000	0.023	0.051	0.050	0.034	0.075
Num. obs.	78	961	45	1012	176	3121

$^{*}p < 0.05$

Table A10: Change in Weighted Probability in Types of Separate Opinion Containing Judicial Activism Claim (Only Authors)

	Concur		Concur on Judgement		Dissent	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Ideological Dist. (Op. Writer)	0.034	0.006	−0.202	0.003	−0.035	**0.016***
	(0.081)	(0.011)	(0.114)	(0.011)	(0.039)	(0.005)
Dist., Sq. (Op. Writer)	−0.005	−0.001	**0.031***	−0.001	0.004	**−0.002***
	(0.012)	(0.001)	(0.014)	(0.001)	(0.005)	(0.001)
Issue Salience	0.000	−0.029	−0.037	**−0.029***	0.018	−0.007
	(0.077)	(0.019)	(0.059)	(0.012)	(0.020)	(0.006)
Personal Salience	0.013		0.064		0.003	
	(0.036)		(0.073)		(0.018)	
Case Complexity	0.022	−0.013	−0.082	−0.010	−0.012	−0.009
	(0.056)	(0.012)	(0.091)	(0.011)	(0.023)	(0.005)
Direction of Dissent					−0.275	−0.049
					(0.225)	(0.035)
Justice Fixed Effects	No	Yes	No	Yes	No	Yes
Issue Area Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.155	0.065	0.352	0.092	0.057	0.090
Adj. R^2	−0.033	0.022	0.080	0.050	0.018	0.076
Num. obs.	78	961	45	1012	176	3121

$^*p < 0.05$

Table A11: Change in Probability in Types of Separate Opinion Containing Judicial Activism Claim

	Concur		Concur on Judgement		Dissent	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Ideological Dist. (Op. Writer)	0.046	0.007	−0.103	0.001	0.002	**0.007***
	(0.043)	(0.006)	(0.070)	(0.006)	(0.018)	(0.003)
Dist., Sq. (Op. Writer)	−0.005	−0.001	**0.017***	−0.001	−0.001	−**0.001***
	(0.007)	(0.001)	(0.008)	(0.001)	(0.003)	(0.000)
Issue Salience	0.035	−0.012	−0.015	−**0.017***	0.003	−0.000
	(0.041)	(0.011)	(0.037)	(0.006)	(0.010)	(0.003)
Personal Salience	0.001		0.031		0.016	
	(0.012)		(0.031)		(0.009)	
Case Complexity	0.005	−0.012	−0.052	−0.010	−0.017	−**0.009***
	(0.028)	(0.006)	(0.053)	(0.006)	(0.012)	(0.003)
Direction of Dissent					−0.186	−0.019
					(0.155)	(0.018)
Justice Fixed Effects	No	Yes	No	Yes	No	Yes
Issue Area Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.163	0.082	0.214	0.082	0.023	0.052
Adj. R^2	0.047	0.052	0.021	0.054	0.005	0.045
Num. obs.	116	1345	67	1538	389	6749

$^{*}p < 0.05$

Table A12: Change in Weighted Probability in Types of Separate Opinion Containing Judicial Activism Claim

	Concur		Concur on Judgement		Dissent	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Ideological Dist. (Op. Writer)	0.060	0.011	−0.136	−0.001	0.008	**0.009***
	(0.066)	(0.009)	(0.080)	(0.009)	(0.024)	(0.004)
Dist., Sq. (Op. Writer)	−0.006	−0.001	**0.019***	−0.001	−0.000	**−0.001***
	(0.010)	(0.001)	(0.009)	(0.001)	(0.003)	(0.000)
Issue Salience	0.065	−0.020	−0.027	**−0.028***	0.009	−0.002
	(0.062)	(0.018)	(0.043)	(0.009)	(0.013)	(0.004)
Personal Salience	0.005		0.029		0.023	
	(0.019)		(0.035)		(0.013)	
Case Complexity	0.033	**−0.020***	−0.048	**−0.020***	−0.011	**−0.009***
	(0.042)	(0.010)	(0.060)	(0.009)	(0.015)	(0.004)
Direction of Dissent					−0.270	−0.033
					(0.207)	(0.026)
Justice Fixed Effects	No	Yes	No	Yes	No	Yes
Issue Area Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.210	0.068	0.284	0.082	0.029	0.047
Adj. R^2	0.101	0.037	0.109	0.055	0.011	0.040
Num. obs.	116	1345	67	1538	389	6746

$^*p < 0.05$

Probit Models

The probit models are the same for both the weighted and non-weighted models. I use a number of controls to model what prior research found influences separate opinion writing. Alongside the ideological distance from either the median in the majority or the majority opinion writer, I include measures of prior-agreement between justices, the types of justices, legal complexity, salience, and whether the justice is more ideologically extreme than the opinion writer in the majority or the median in the majority. I do not account for workload since prior research suggests that the workload influences the likelihood a justice will author an opinion (Epstein, Landes, and Posner 2011; Wahlbeck, Spriggs, and Maltzman 1999). I create a binary indicator of whether a Justice is the Chief of the court, and a binary indicator for freshman Justices who have been on the Supreme Court for fewer than two terms. Minimum coalition size is controlled for with a dichotomous variable indicating if the majority is the minimum winning coalition size.

Justices who cooperated with each other in the past are less likely to write separate opinions when one of them are the opinion writer for the majority opinion, suggesting that prior agreement influences when to write a separate opinion. The prior agreement between justices is measured by first calculating proportion a Justice has joined another Justice's separate opinion per term over the Justice's total number of authored separate opinions. I then calculate the absolute distance in the two justices' Martin Quinn scores (Martin and Quinn 2002). I regress the proportion each justice joined each other Justice's separate opinion on the absolute difference in their Martin Quinn scores, and create the measure of cooperation using the residuals from that regression. A negative value signals that two justices do not agree as much as is expected, while positive numbers signal justices agree with each other more than expected.

Table A13: Probit Results for Writing a Separate Opinion

	Dependent variable:			
	Sep. Opinion, Wrote or Joined		Sep. Opinion, Wrote Only	
	(1)	(2)	(3)	(4)
Distance to Median in Maj.	0.241*		0.139*	
	(0.004)		(0.004)	
Distance to Maj. Opinion Writer		0.117*		0.075*
		(0.003)		(0.004)
Chief Justice	0.029	−0.252*	−0.277*	−0.439*
	(0.025)	(0.023)	(0.029)	(0.028)
Case Complexity	0.027*	0.020*	0.038*	0.033*
	(0.010)	(0.010)	(0.011)	(0.010)
Issue Salience	0.148*	0.149*	0.162*	0.166*
	(0.011)	(0.010)	(0.011)	(0.011)
Freshman Term	0.057*	−0.138*	−0.014	−0.132*
	(0.027)	(0.026)	(0.030)	(0.029)
Minimum Winning Coalition	0.712*	0.809*	0.224*	0.310*
	(0.017)	(0.017)	(0.018)	(0.018)
More Extreme than Median in Maj.	−0.482*		−0.269*	
	(0.015)		(0.017)	
More Extreme than Opinion Writer		0.016		0.076*
		(0.017)		(0.019)
Prior Agreement	−1.192*	−0.854*	−1.156*	−0.981*
	(0.046)	(0.043)	(0.056)	(0.055)
Constant	−0.931*	−0.946*	−1.154*	−1.193*
	(0.016)	(0.017)	(0.017)	(0.018)
Observations	40,818	40,818	40,818	40,818
Log Likelihood	−21,723.790	−23,435.960	−18,267.060	−18,758.150
χ^2 (df = 8)	7,989.744*	4,565.403*	2,680.974*	1,698.800*
Note:				$^*p < 0.05$

Table A14: Probit Results for Writing a Concurrence

	Dependent variable:			
	Concur, Wrote or Joined		Concur, Wrote Only	
	(1)	(2)	(3)	(4)
Distance to Median in Maj.	−0.022*		−0.026*	
	(0.007)		(0.008)	
Distance to Maj. Opinion Writer		0.012*		0.002
		(0.005)		(0.006)
Chief Justice	−0.261*	−0.207*	−0.334*	−0.292*
	(0.040)	(0.039)	(0.048)	(0.047)
Case Complexity	0.014	0.014	0.015	0.015
	(0.015)	(0.015)	(0.017)	(0.017)
Issue Salience	0.167*	0.167*	0.164*	0.163*
	(0.016)	(0.015)	(0.017)	(0.017)
Freshman Term	−0.007	0.031	−0.039	−0.008
	(0.040)	(0.039)	(0.045)	(0.044)
Minimum Winning Coalition	−0.030	−0.056*	0.044	0.016
	(0.028)	(0.028)	(0.030)	(0.030)
More Extreme than Median in Maj.	0.130*		0.119*	
	(0.023)		(0.025)	
More Extreme than Opinion Writer		0.129*		0.143*
		(0.026)		(0.028)
Prior Agreement	−0.190*	−0.273*	−0.310*	−0.405*
	(0.060)	(0.063)	(0.075)	(0.077)
Constant	−1.664*	−1.720*	−1.811*	−1.852*
	(0.024)	(0.026)	(0.027)	(0.029)
Observations	40,818	40,818	40,818	40,818
Log Likelihood	−7,848.101	−7,859.649	−6,187.098	−6,193.121
χ^2 (df = 8)	214.638*	191.543*	211.964*	199.918*
Note:				$^{*}p < 0.05$

Table A15: Probit Results for Writing a Concurrence in the Judgement

	Dependent variable:			
	Concur in Jud., Wrote or Joined		Concur in Jud., Wrote Only	
	(1)	(2)	(3)	(4)
Distance to Median in Maj.	0.030*		0.016*	
	(0.006)		(0.007)	
Distance to Maj. Opinion Writer		0.054*		0.040*
		(0.005)		(0.006)
Chief Justice	−0.241*	−0.208*	−0.388*	−0.372*
	(0.040)	(0.039)	(0.051)	(0.050)
Case Complexity	0.046*	0.045*	0.043*	0.042*
	(0.015)	(0.015)	(0.016)	(0.016)
Issue Salience	0.146*	0.149*	0.149*	0.151*
	(0.015)	(0.015)	(0.017)	(0.017)
Freshman Term	−0.074	−0.055	−0.094*	−0.079
	(0.041)	(0.040)	(0.047)	(0.046)
Minimum Winning Coalition	−0.536*	−0.525*	−0.466*	−0.457*
	(0.035)	(0.034)	(0.038)	(0.038)
More Extreme than Median in Maj.	0.069*		0.025	
	(0.022)		(0.025)	
More Extreme than Opinion Writer		−0.029		−0.012
		(0.027)		(0.031)
Prior Agreement	−0.882*	−0.984*	−0.954*	−1.098*
	(0.081)	(0.088)	(0.098)	(0.107)
Constant	−1.630*	−1.706*	−1.764*	−1.847*
	(0.024)	(0.026)	(0.027)	(0.030)
Observations	40,818	40,818	40,818	40,818
Log Likelihood	−8,677.194	−8,625.323	−6,597.428	−6,573.231
χ^2 (df = 8)	607.993*	711.735*	479.054*	527.449*
Note:				$^*p < 0.05$

Table A16: Probit Results for Writing a Dissenting Opinion

	Dependent variable:			
	Dissent, Wrote or Joined		Dissent, Wrote Only	
	(1)	(2)	(3)	(4)
Distance to Median in Maj.	0.293*		0.195*	
	(0.005)		(0.005)	
Distance to Maj. Opinion Writer		0.120*		0.089*
		(0.004)		(0.004)
Chief Justice	0.245*	−0.173*	−0.102*	−0.363*
	(0.029)	(0.025)	(0.036)	(0.033)
Case Complexity	0.008	0.001	0.028*	0.021
	(0.011)	(0.010)	(0.013)	(0.012)
Issue Salience	0.036*	0.053*	0.080*	0.091*
	(0.012)	(0.011)	(0.013)	(0.013)
Freshman Term	0.116*	−0.168*	0.053	−0.150*
	(0.032)	(0.029)	(0.036)	(0.035)
Minimum Winning Coalition	0.991*	1.057*	0.424*	0.538*
	(0.019)	(0.017)	(0.020)	(0.019)
More Extreme than Median in Maj.	−0.805*		−0.523*	
	(0.019)		(0.022)	
More Extreme than Opinion Writer		−0.004		0.056*
		(0.019)		(0.022)
Prior Agreement	−1.210*	−0.707*	−1.257*	−0.865*
	(0.055)	(0.048)	(0.073)	(0.067)
Constant	−1.431*	−1.352*	−1.646*	−1.627*
	(0.019)	(0.018)	(0.021)	(0.022)
Observations	40,818	40,818	40,818	40,818
Log Likelihood	−16,006.690	−18,752.150	−12,303.150	−13,280.740
χ^2 (df = 8)	10,797.960*	5,307.044*	3,598.174*	1,642.991*
Note:				$^*p < 0.05$

Appendix References

Chen, Tianqi, and Carlos Guestrin. 2016. "XGBoost: A Scalable Tree Boosting System." In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 785–94.

Green, Craig. 2009. "An Intellectual History of Judicial Activism." https://papers.ssrn.com/abstract=1410728.

Kmiec, Keenan D. 2004. "The Origin and Current Meanings of 'Judicial Activism'." *California Law Review* 92(5): 1441.

Lindquist, Stefanie A., and Frank B. Cross. 2009. *Measuring Judicial Activism*. New York: Oxford Univ. Press.

Martin, Andrew D., and Kevin M. Quinn. 2002. "Dynamic Ideal Point Estimation via Markov Chain Monte Carlo for the U.S. Supreme Court, 1953–1999." *Political Analysis* 10(2): 134–53.

Wahlbeck, Paul J., James F. Spriggs, and Forrest Maltzman. 1999. "The Politics of Dissents and Concurrences on the U.S. Supreme Court." *American Politics Quarterly* 27(4): 488–514.

Zheng, Wanwan, and Mingzhe Jin. 2020. "The Effects of Class Imbalance and Training Data Size on Classifier Learning: An Empirical Study." *SN Computer Science* 1(2): 71.