Supplemental Material (not copyedited or formatted) for: Joshua Boston. 2020.
"Strategic Opinion Language on the U.S. Courts of Appeals."
Journal of Law and Courts 8(1). DOI: https://doi.org/10.1086/704633.

Strategic Opinion Language on the U.S. Courts of Appeals

Online Appendix

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September 10, 2019

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10 Appendices

10.1 Identifying Theoretical Expectations

Table 1: Identifying Circuit Court Opinion Language Strategies

		Circuit Court Precedent Treatment	
		Positive	Negative
U.S. Supreme Court	Likes	Low Complexity	High Complexity
Precedent Preferences	Dislikes	High Complexity	Low Complexity

The hypotheses outlined in the main manuscript attempt to describe the relationship between (a) Supreme Court preferences, (b) precedent treatment, and (c) opinion complexity. Given the continuous nature of two out of three of those variables, Table 1 does not identify the entire span of possibilities across both ideological distance and opinion complexity. When the circuit panel positively treats a Supreme Court precedent, and as the Supreme Court bench median increasingly dislikes that precedent, I expect increasing levels of opinion complexity; that hypothesis (i.e. the Positive Treatment Hypothesis) is detailed by the upper-left and lower-left quadrants of Table 1 above. When the circuit panel negatively treats a Supreme Court precedent, and the Supreme Court median increasingly prefers that precedent, I expect increasing levels of opinion complexity; that hypothesis (i.e. the Negative Treatment Hypothesis) is detailed by the upper-right and lower-right quadrants of Table 1.

Positive Treatment Hypothesis: *The complexity of a circuit court opinion will increase when the circuit panel positively treats a precedent, and the Supreme Court increasingly dislikes that precedent.*

Negative Treatment Hypothesis: *The complexity of a circuit court opinion will increase when the circuit panel negatively treats a precedent, and the Supreme Court* *increasingly prefers that precedent.*

Rather than specifying the increasing nature of complexity under certain conditions, I could have alternatively specified four distinct hypotheses in something like the following way: "When the circuit court [negatively/positively] treats a Supreme Court precedent that the Court's median justice [likes/dislikes], circuit opinion complexity should be [high/low]." But, I think sacrificing the dynamic nature of both opinion complexity and the Supreme Court median's preferences for the simplified hypotheses gets away from the interplay of the different conditions.

10.2 Understanding the Interaction Terms

Table 2 in the main portion of the paper utilizes three explanatory variables to examine the hypotheses regarding circuit court opinion complexity: *Distance from Supreme Court to Precedent*, *Negative Treatment*, and an interaction of those two variables. To reiterate the findings with regard to Table 2, *Distance from Supreme Court to Precedent* indicates the amount of opinion complexity when *Negative Treatment* is zero – that is, when the circuit is positively treating the Supreme Court precedent in question. Therefore, as the Supreme Court median increasingly dislikes the precedent in question and the circuit panel is positively treating that precedent, opinion complexity increases. When *Negative Treatment* is present and *Distance from Supreme Court to Precedent* is equal to zero (i.e. the Supreme Court median highly prefers the precedent), the *Negative Treatment* variable indicates increasing circuit court opinion complexity. Finally, when *Negative Treatment* is present and the Supreme Court median increasingly dislikes the precedent (i.e. *Distance from Supreme Court to Precedent* increases), the interaction term – along with the component variables – shows that complexity decreases as the circuit panel is less concerned about insulating the treatment in question. These results hold across all four columns in Table 2, though *Negative Treatment* is only statistically significant in one of those empirical estimations.

Of course, parsing out the meaning of interaction terms can sometimes be complicated. In order to ensure that my interpretations of these and other complex variables are understandable, I more deeply describe some of the results below. In order to achieve this, I present some additional

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models. First, I examine empirical estimations without any interaction variables. To achieve this, I subset the data by precedent treatment and regress *Complexity of Court Opinion* on *Distance from Supreme Court to Precedent* for each type of precedent treatment. Second, I more deeply examine some complex interaction terms in order to investigate how Supreme Court and circuit court precedent preferences influence opinion complexity. I am genuinely thankful to the anonymous reviewers and journal editor for suggesting these additional empirical models.

10.2.1 Bivariate Regressions with Subsetted Precedent Data

The empirical estimations in Table 2 correspond directly to the plots in Figure 1 above. Despite the fact that the slopes in Figure 1 and the coefficients in each column of Table 2 are all in the substantively appropriate directions, only the models for *Positive Treatment* and *Positive and Neutral Treatment* achieve statistical significance, which is likely a result of the size of the datasets.

Table 2: Regression Estimations of Opinion Complexity Across Data Subsets

	Outcome Variable: Complexity of Court Opinion (subsets)			
	Negative Treatment	*Neutral Treatment*	*Positive Treatment*	*Pos. & Neu. Treatment*
Distance from Supreme Court to Precedent	-0.464	0.0277	1.048**	0.763*
	(0.452)	(0.579)	(0.392)	(0.325)
Constant	0.102	0.241	-0.332**	-0.164
	(0.133)	(0.159)	(0.106)	(0.0880)
Observations	2861	2115	4821	6936

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

10.2.2 Examining Additional Interaction Variables

Table 3 below examines preference interactions between the Supreme Court, circuit court panels, and the precedent-enacting Supreme Court majority coalition. These empirical estimations help to answer previously unexplored questions, which serve as robustness checks to the models presented

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in the main body of this manuscript. To be clear, these models do not necessarily test the established hypotheses, though I would not expect the estimations to contradict any of the predicted relationships. For instance, how might we expect opinion complexity to change under negative treatment, as both the Supreme Court and the circuit court panel increasingly dislike the precedent in question? Surely, opinion complexity should decrease under those conditions.

To answer questions like this, I interact three variables in each of the first three models (columns 1, 2 and 3 of Table 3). Each of these columns contains a different triple interaction including *Negative Treatment* and two of the preference distance measures. The final column of Table 3 includes all of the interaction terms. Importantly, in all three columns of Table 3, *Distance from Supreme Court to Precedent* (which is omitted from column 3) is positive and statistically significant, indicating that given positive or neutral treatment by the circuit panel, as the Supreme Court median justice increasingly dislikes that precedent, the circuit panel writes its opinion with greater complexity. These findings provide further evidence in support of the Positive Treatment Hypothesis.

The example question given above – whether Supreme Court and circuit panel precedent preferences influence opinion complexity under certain precedent treatment – is addressed in column 1 of Table 3. Consistent with previously estimations, *Distance from Panel to Precedent* – a measure of the circuit median's (or two-judge midpoint) ideological distance from the Supreme Court precedent – does not attain statistical significance. Even if it were, it is difficult to discern substantive expectations given the multitude of conditions.

The coefficient estimate for the triple interaction reveals some intriguing empirical results; given negative precedent treatment by the circuit court, as both the Supreme Court and circuit panel increasingly dislike the precedent in question, we observe a statistically significant decrease in opinion complexity. It is unlikely that the -1.934 result is driven exclusively by the preferences of one of the actors – that is, the Supreme Court *or* the circuit court. Rather, it seems much more likely that the result is due to a pairwise increases in both variables, given that a low value for either variable would diminish the overall value. Of course it is possible that one of the two variables could increase more rapidly than the other. But generally speaking, both must increase – to some extent – in order for the interaction to differentiate.

Table 3: OLS Regression Estimations of Opinion Complexity with Triple Interactions

	Outcome Variable: Complexity of Court Opinion			
	(1)	(2)	(3)	(4)
Negative Treatment	−0.266	0.358	0.555	0.267
	(0.277)	(0.292)	(0.293)	(0.339)
Distance from Supreme Court to Precedent	−0.004	1.097		0.415
	(0.572)	(0.579)		(0.846)
Distance from Panel to Precedent	−0.376		0.782	−0.788
	(0.431)		(0.497)	(0.835)
Distance from Supreme Court to Panel		0.229	0.172	0.660
		(0.540)	(0.583)	(0.862)
Distance from Supreme Court to Precedent × Distance from Panel to Precedent	1.905 (1.259)			2.548 (1.524)
Distance from Supreme Court to Precedent × Distance from Supreme Court to Panel		−1.377 (1.991)		−2.305 (2.411)
Distance from Panel to Precedent × Distance from Supreme Court to Panel			−1.346 (1.474)	0.182 (1.782)
Negative Treatment × Distance from Supreme Court to Precedent	0.822 (0.986)	−1.691 (1.036)		0.959 (1.475)
Negative Treatment × Distance from Panel to Precedent	1.678* (0.788)		−2.164* (0.898)	1.690 (1.518)
Negative Treatment × Distance from Supreme Court to Panel		−0.374 (0.984)	−1.726 (1.049)	−4.489* (1.598)
Negative Treatment × Distance from Supreme Court to Precedent × Distance from Panel to Precedent	−5.524* (2.115)			−9.296* (2.625)
Negative Treatment × Distance from Supreme Court to Precedent × Distance from Supreme Court to Panel		1.889 (3.473)		6.484 (4.315)
Negative Treatment × Distance from Panel to Precedent × Distance from Supreme Court to Panel			5.942* (2.616)	5.437 (3.184)
Constant	−0.029	−0.220	−0.158	−0.100
	(0.149)	(0.157)	(0.156)	(0.184)
Observations	9,797	9,797	9,797	9,797
Akaike Inf. Crit.	55,990.39	55,997.2	55,996.58	55,992.52
Bayesian Inf. Crit.	56,055.1	56,061.91	56,061.29	56,100.37

Note: *p<0.05

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10.3 Alternative Reference Category: Including Neutral Precedent Treatment

Table 4 and Figure 2 which follow include neutral precedent treatment in the analysis, creating a new reference category for *Negative Treatment*; zero values represent positive *and* neutral precedent treatment.

Table 4: Regression Estimations of Opinion Complexity Including Neutral Treatment

	Outcome Variable: Complexity of Court Opinion			
	OLS	*Linear Mixed Effects*	*OLS*	*Linear Mixed Effects*
	(1)	(2)	(3)	(4)
Distance from Supreme Court to Precedent	0.763*	1.449*	0.671*	1.400*
	(0.321)	(0.439)	(0.341)	(0.447)
Negative Treatment	0.266	0.394*	0.257	0.328
	(0.162)	(0.164)	(0.218)	(0.216)
Negative Treatment	−1.227*	−1.488*	−1.206*	−1.431*
× Distance from Supreme Court to Precedent	(0.567)	(0.573)	(0.605)	(0.604)
Distance from Panel to Precedent	–	–	0.211	0.147
	–	–	(0.266)	(0.257)
Distance from Supreme Court to Panel	–	–	−0.176	−0.098
	–	–	(0.340)	(0.326)
Negative Treatment	–	–	0.087	0.396
× Distance from Supreme Court to Panel	–	–	(0.605)	(0.578)
Negative Treatment	–	–	−0.056	−0.147
× Distance from Panel to Precedent	–	–	(0.471)	(0.452)
Constant	−0.164*	−0.496*	−0.165	−0.506*
	(0.087)	(0.135)	(0.118)	(0.157)
Random effects:				
Supreme Court Precedent	–	2.085	–	2.086
	–	(1.444)	–	(1.444)
Observations	9,797	9,797	9,797	9,797
Akaike Inf. Crit.	55,989.77	55,287.74	55,996.92	55,296.27
Bayesian Inf. Crit.	56,025.72	55,330.87	56,061.63	55,368.17

Multilevel model estimations allow for random intercepts across the 422 Supreme Court precedents cited by the circuit court opinions.
Note: $^{*}p<0.05$

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Figure 2: Opinion Comlexity, Supreme Court Preferences & Circuit Precedent Treatment

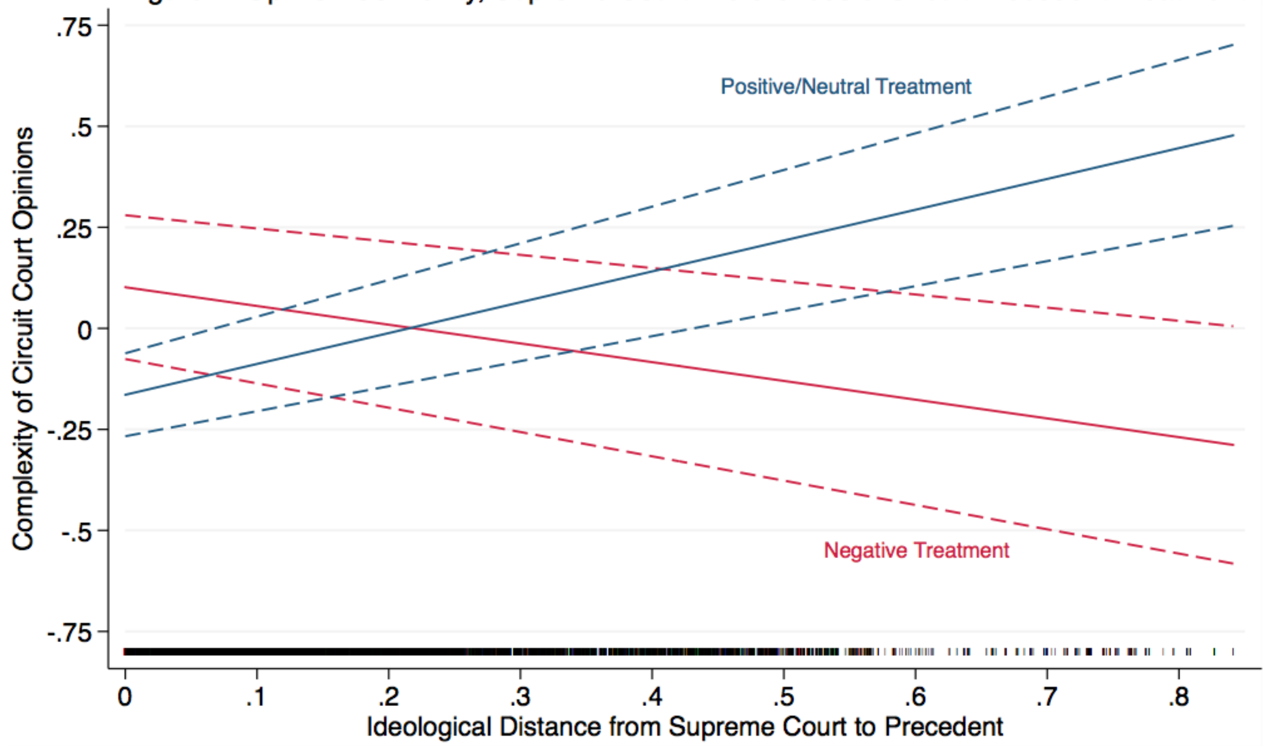

Table 4 and Figure 2 above estimate empirical models of opinion complexity including neutral treatment in the *Negative Treatment* reference category. The coefficients for *Distance from Supreme Court to Precedent* change slightly in comparison to those in Table 2 in the main text, but it is difficult to tell whether those differences are statistically distinguishable. If they are, I have stronger evidence that positive precedent treatment leads to increases in opinion complexity at the Supreme Court increasingly dislikes its precedent. Furthermore, the coefficients for *Negative Treatment* lose statistical significance, which they had achieved in Table 2. This provides weaker evidence that when (1) the circuit opinion negatively treats a Supreme Court precedent and (2) the Supreme Court median highly prefers that precedent, we observe higher levels of opinion complexity from the circuit panel. In the end, the inclusion of neutral treatment cases is somewhat perplexing, since it is unclear what expectations we should have about how circuit judges might insulate neutral treatment. Some scholars (e.g. Hinkle 2015) have suggested that neutral treatments are “soft positives,” since the treatment goes beyond a mere string citation and it does not distinguish the instant case’s facts from the precedent.

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This is made even clearer when we compare the degree of confidence interval overlap between Figures 1 and 2. On the left-hand side of Figure 2 (at low levels of ideological distance, indicating highly preferred precedents), the negative and positive treatment lines are statistically indistinguishable, whereas in Figure 2 in the main text, they are distinct. This is the result of including (or not) neutral treatment cases.

10.4 Alternative Outcome Variables

The regression estimations that follow are specified using alternative outcome variables. First, Table 5 provides seven new model estimations along with the original multilevel random effects model from Column 2 of Table 2 in the main manuscript above. The seven new models utilize somewhat different outcome variables, as each one omits a single LIWC element from the complexity factor score. For instance, Column 2 of Table 5 omits the Cause element of the *Complexity of Court Opinion* factor scores. Columns 2 through 8 of Table 5 omit (2) cause, (3) certainty, (4) differentiation, (5) discrepancies, (6) insight, (7) negations, and (8) tentativeness, respectively. Interestingly, the results are stable across all of these specifications, suggesting that the variation in complexity is not attributable to any single LIWC category. The explanatory variables of interest all find statistical and substantive significance.

Table 6 takes a somewhat different approach to specifying outcome variables for each model; each model predicts an individual LIWC elements independent of the other six categories. For instance, Column 1 of Table 6 predicts the LIWC category cause, and we can see that not all of the explanatory variables have the effect we would expect; only *Distance from Supreme Court to Precedent* is in the expected direction, suggesting that – given positive precedent treatment by the circuit panel – as the Supreme Court increasingly dislikes its precedent, the circuit panel authors a more complex opinion. The results vary across all seven models, with only the Tentativeness model in Column 7 of Table 6 not achieving any statistically significant explanatory variables. This table is meant, yet again, to show that the individual LIWC categories do not fully capture cognitive complexity.

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Table 5: Random Effects Multilevel Regression Estimations of Opinion Complexity Omitting Individual Complexity Components

	Outcome Variable: Complexity of Court Opinion Omitting Certain Components							
	Full Scale (1)	No Cause (2)	No Certainty (3)	No Differentiation (4)	No Discrepancies (5)	No Insight (6)	No Negations (7)	No Tentativeness (8)
Distance from Supreme Court to Precedent	1.449*	1.091*	1.139*	1.354*	1.090*	0.939*	1.749*	1.386*
	(0.439)	(0.389)	(0.386)	(0.371)	(0.380)	(0.388)	(0.395)	(0.385)
Negative Treatment	0.394*	0.346*	0.308*	0.275*	0.367*	0.419*	0.311*	0.342*
	(0.164)	(0.146)	(0.145)	(0.136)	(0.141)	(0.148)	(0.146)	(0.142)
Negative Treatment × Distance from Supreme Court to Precedent	-1.488*	-1.276*	-1.102*	-1.209*	-1.166*	-1.267*	-1.618*	-1.292*
	(0.573)	(0.510)	(0.508)	(0.476)	(0.494)	(0.518)	(0.512)	(0.499)
Constant	-0.496*	-0.486*	-0.399*	-0.513*	-0.412*	-0.208	-0.500*	-0.479*
	(0.135)	(0.119)	(0.118)	(0.118)	(0.118)	(0.116)	(0.123)	(0.120)
Random effects:								
Supreme Court Precedent	2.085	1.582	1.494	1.82	1.672	1.294	1.85	1.741
	(1.444)	(1.258)	(1.222)	(1.349)	(1.293)	(1.138)	(1.360)	(1.320)
Observations	9797	9797	9797	9797	9797	9797	9797	9797
Akaike Inf. Crit.	55,287.74	52,995.46	52,938.69	51,655.24	52,369.74	53,320.79	53,053.01	52,557.17
Bayesian Inf. Crit.	55,330.87	53,038.6	52,981.83	51,698.38	52,412.88	53,363.93	53,096.15	52,600.31

Multilevel model estimations allow for random intercepts across the 422 Supreme Court precedents cited by the circuit court opinions.
Note: $^{*}p<0.05$

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Table 6: Random Effects Multilevel Regression Estimations of Individual Complexity Components

	Outcome Variable: Individual LIWC Components						
	Cause	Certainty	Differ	Discrepancy	Insight	Negations	Tenativeness
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Distance from Supreme Court to Precedent	0.450*	0.285*	0.161	0.380*	0.521*	-0.250*	0.105
	(0.107)	(0.105)	(0.104)	(0.105)	(0.0967)	(0.0998)	(0.104)
Negative Treatment	0.0558	0.0836*	0.123*	0.0274	-0.0172	0.0862*	0.0568
	(0.0381)	(0.0385)	(0.0392)	(0.0390)	(0.0334)	(0.0389)	(0.0394)
Negative Treatment × Distance from Supreme Court to Precedent	-0.234	-0.383*	-0.282*	-0.323*	-0.207	0.129	-0.209
	(0.134)	(0.135)	(0.137)	(0.137)	(0.117)	(0.136)	(0.138)
Constant	-0.0213	-0.0918*	-0.000665	-0.0882*	-0.320*	-0.0115	-0.0284
	(0.0364)	(0.0329)	(0.0313)	(0.0323)	(0.0369)	(0.0292)	(0.0311)
Random effects:							
Supreme Court Precedent	0.223	0.137	0.100	0.119	0.300	0.068	0.094
	(0.472)	(0.370)	(0.316)	(0.345)	(0.545)	(0.261)	(0.306)
Observations	9797	9797	9797	9797	9797	9797	9797
Akaike Inf. Crit.	26,746.54	26,949.01	27,325.75	27,196.24	24,240.17	27,187.61	27,418.69
Bayesian Inf. Crit.	26,789.68	26,992.15	27,368.88	27,239.38	24,283.31	27,230.75	27,461.83

Multilevel model estimations allow for random intercepts across the 422 Supreme Court precedents cited by the circuit court opinions.
Note: $^{*}p<0.05$

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10.5 Legal Issue Complexity

In Table 7 below, I examine several different operationalizations of circuit court case or legal complexity as a control variable in determining the relationship between the explanatory variables of interest and the outcome variable: opinion complexity. Importantly, legal complexity is conceptually distinct from textual opinion complexity. The former – legal complexity – concerns "the number of legal concepts involved in a case" (Moyer 2012, 299, citing Johnson 1987), which scholars typically measure by conducting a factor analysis of the issues and opinion length (e.g. Lindquist, Martinek, & Hettinger 2007). Opinion complexity, as I and others have conceptualized it Owens, Wedeking, & Wohlfarth (e.g. 2013), ultimately concerns the words used in an opinion, and those words correspond to the "clarity of the ideas discussed" (Owens & Wedeking 2012). It seems logical to expect that a more legally complex case – that is, a case that crosses into several or many different legal issue areas – might also have a less conceptually clear opinion, since judges are often forced to address multifaceted legal issues.

Notwithstanding the expected relationship between legal issue complexity and textual opinion complexity, this research aims to provide evidence that other conditions also help to explain the variation in circuit court opinion complexity. Among those explanatory variables are precedent treatment and the Supreme Court's preferences for the precedent. I do not expect that legal issue complexity is related to these explanatory variables, and, therefore, issue complexity is not a traditional "control variable."[1]

As legal issue complexity was not the primary focus of my paper, and since it is unlikely to correlate with my explanatory variables of interest, I did not include it in the main models of the paper. I nonetheless estimate several different empirical models – for robustness checks – to examine the influence of legal complexity on opinion complexity. Column 1 in Table 7 is the

[1] Omitted variable bias occurs when a "control variable" absent from the original empirical estimation is (a) correlated with the right hand side (i.e. explanatory) variables and (b) a significant predictor of the outcome variable. (See, for example, `www.kellogg.northwestern.edu/faculty/dranove/htm/dranove/coursepages/Mgmt\%20469/choosing\%20variables.pdf`) If one of these conditions is absent regarding the omitted variable, then there is no bias resulting in the more parsimonious model. That is not to say that other factors could not introduce bias into the model.

baseline model; the results presented there are identical to column 2 in Table 2 in the main text. Column 2 in Table 7 includes the standardized word count of the circuit court opinion, which serves as a proxy measure for the circuit court case's legal issue complexity. Generally speaking, we would think that a long opinion arises out of a case that is more legally complex – that is to say, a case in which a judge must address more legal issues. In turn, the legally complex case leading to a longer opinion also corresponds with an increase in textual opinion complexity, sincere the opinion is less conceptually clear than, perhaps, a single-legal-issue case. As we see in Column 2, this is the exact relationship I find, where an increase in *Opinion Word Count* leads to increased complexity. Nonetheless, the expected relationships with the explanatory variables of interest (*Distance from Supreme Court to Precedent*, *Negative Treatment*, and the interaction term) all remain in their substantively expected directions. Only *Negative Treatment* falls away from statistical significance in comparison to Column 1, though we can see from *Negative Treatment's* standard error in Column 2 that this is close to a borderline case.

Column 3 in Table 7 includes the Supreme Court precedent's issue complexity, as directly borrowed from Westerland et al. (2010). In this instance, the issue complexity of the Supreme Court precedent (which is the one the circuit court is treating) serves as a rough proxy measure of the circuit court issue complexity.[2] Perhaps interestingly, in comparing the proxy measures for issue complexity, the pairwise correlation of circuit court opinion word count and the Supreme Court issue complexity is 0.0045. Still, the empirical estimation results for *Supreme Court Precedent Issue Complexity* in Column 3 do not compare to the *Opinion Word Count* result in Column 2. *Supreme Court Precedent Issue Complexity* does not approach statistical significance, and the results from the original model in Column 1 completely hold.

[2]From Westerland et al. (2010, 896): "We code issue complexity as the number of legal provisions plus the number of legal issues present in the precedent as coded directly from Spaeth's U.S. Supreme Court Database." (Spaeth et al. 2017)

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Table 7: Random Mixed Effects Multilevel Regression Estimations including Case Issue Complexity

	Outcome Variable: Complexity of Court Opinion					
	(1)	(2)	(3)	(4)	(5)	(6)
Distance from Supreme Court to Precedent	1.449*	0.871*	1.485*	−1.377	0.869*	0.883*
	(0.439)	(0.421)	(0.440)	(1.287)	(0.431)	(0.423)
Negative Treatment	0.394*	0.303	0.393*	0.462	0.349*	0.302
	(0.164)	(0.158)	(0.164)	(0.598)	(0.161)	(0.158)
Negative Treatment × Distance from Supreme Court to Precedent	−1.488*	−1.188*	−1.484*	−1.419	−1.377*	−1.185*
	(0.573)	(0.553)	(0.573)	(2.078)	(0.565)	(0.553)
Opinion Word Count (standardized)	–	1.100*	–	–	–	1.067*
	–	(0.041)	–	–	–	(0.053)
Supreme Court Precedent Issue Complexity	–	–	−0.139	–	–	−0.131
	–	–	(0.113)	–	–	(0.106)
Circuit Court Case Issue Complexity	–	–	–	0.399*	0.726*	0.052
	–	–	–	(0.102)	(0.042)	(0.053)
Constant	−0.496*	−0.436*	−0.189	−0.434	−1.797*	−0.241
	(0.135)	(0.128)	(0.284)	(0.389)	(0.152)	(0.290)
Random Effects:						
Supreme Court Precedent	2.085	1.785	2.081	0.643	1.891	1.776
	(1.444)	(1.336)	(1.442)	(0.802)	(1.375)	(1.333)
Observations	9,797	9,797	9,797	647	9,797	9,797
Akaike Inf. Crit.	55,287.740	54,602.830	55,290.750	3,646.749	54,998.620	54,610.850
Bayesian Inf. Crit.	55,330.870	54,653.160	55,341.080	3,678.056	55,048.950	54,675.560

Note: *p<0.05

Columns 4, 5 and 6 in Table 7 attempt to get directly at the legal issue complexity of each circuit court case. To achieve this, I used the data method outlined in Moyer (2012), who originally coded a legal complexity variable for all cases in the the United States Courts of Appeals Database (Songer, Kuersten, & Haire n.d.). This process is highly similar – if not identical – to the issue coding used commonly with the U.S. Supreme Court Database as is presented in Column 3 of Table 7. Unfortunately, since the U.S. Courts of Appeals publish tens of thousands of opinions each year, it is not possible for the Courts of Appeals Database researchers to code every single case across many variables.[3] Therefore, they only code a sample of cases, which causes there to be fairly narrow overlap between the (Songer, Kuersten, & Haire n.d.) data and the data I utilize in this research. In all, only 647 cases are present in both datasets.

For the 647 overlapping cases, I create an additive variable for each unique area of law that is present in a given circuit case. This variable stems from 51 civil and criminal issue variables in the Songer et al. (n.d.) data.[4] The final variable – *Circuit Court Case Issue Complexity* – ranges from 0 to 11, with a mean of 1.96136. I present the empirical estimation results for these 647 cases in Column 4 of Table 7. As we can see from the reduced n for the estimation, the standard errors for my explanatory variables of interest are much larger than normal. Indeed, none of the variables even approach statistical significance. That being said, we do see the expected relationship between *Circuit Court Case Issue Complexity* and the outcome variable; as *Circuit Court Case Issue Complexity* increases, so too does circuit court opinion complexity.

While the *Circuit Court Case Issue Complexity* variable introduced in Column 4 of Table 7 is arguably the most accurate way to capture actual issue complexity, the reduced sample of circuit court cases poses a challenge for understanding the effect of the explanatory variables of interest. In order to better capture whether the expected substantive effects of those variables hold given the issue complexity variable, I use multiple imputation to fill out the missing data. I conducted both

[3]The initial phase of data gathering for the Courts of Appeals Database, which covered cases from 1925 to 1996, included 221 variables, of which 51 were particular legal issue areas falling under civil and criminal umbrellas.

[4]A list of these issue areas is available in the appendix for Moyer (2012) and here: `http://artsandsciences.sc.edu/poli/juri/cta96_codebook.pdf`.

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Journal of Law and Courts 8(1). DOI: https://doi.org/10.1086/704633.

5 and 94 imputations using STATA's `mi impute` command.[5] The results did not greatly differ across the number of imputations.

The results using the imputed data are presented in Column 5 of Table 7. With the increased n, the explanatory variables of interest return to statistical significance in the substantively expected directions; though the magnitude, for instance, of *Distance from Supreme Court to Precedent* in Column 5 does not meet Column 1's benchmark, the results are still strong. Furthermore, the results for *Circuit Court Case Issue Complexity* improve in substantive significance in Column 5 as compared to Column 4. And, importantly, despite the significance of *Circuit Court Case Issue Complexity*, the hypothesized relationships hold.

The same can be said in Column 6 of Table 7, where the results of a more saturated model estimation are largely comparable to Column 5, with one exception: *Circuit Court Case Issue Complexity* loses its substantive and statistical significance in the face of *Opinion Word Count*, which has similar substantive effects as it did in the Column 2 model. Interestingly – likely as a result of the specific imputation model I utilized – word count and issue complexity correlated at a relatively high rate (0.638).[6]

Across the 5 different model specifications that include some direct or proxy measures for issue complexity, I can conclude that, while issue complexity certainly helps to predict textual opinion complexity, its presence in model estimations does not entirely take away the significance of the variables of interest in this research. Therefore, I am confident in saying that opinion complexity is not entirely a byproduct of case conditions, and there is a significant roll for strategic behavior by circuit court judges.

[5] While common practice suggested conducting between 5 and 10 imputations is sufficient, Bodner (2008) "recommends having as many imputations as the percentage of missing data." (See: `https://www.theanalysisfactor.com/multiple-imputation-5-recent-findings-that-change-how-to-use-it/`) As my data missingness is approximately 94 percent ($\frac{647}{9797} = 0.066$), I used 94 imputations.

[6] I conducted other imputations with different model specifications, and it is possible to attain a final model estimation in which the explanatory variables of interest are in the hypothesized directions and are statistically significant, while word count and issue complexity do not correlate.

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10.6 Opinion Complexity and Precedent Vitality

This research has operationalized Supreme Court precedent preferences as the ideological distance from the Supreme Court median to the median of the Supreme Court coalition that issued the precedent. It is possible that a stronger signal from the Supreme Court to the circuit court panel regarding how much the justices value a particular precedent occurs through the Court's prior treatments of the precedent in question. The more often the Court treats its precedent positively, the signal to lower courts is that the precedent is valued by the court, and, furthermore, the precedent has some degree of vitality or authoritativeness (e.g Hansford & Spriggs 2006). The opposite would be true given frequent negative treatment. To combine these considerations, Hansford & Spriggs (2006) introduced the concept of precedent vitality, which attempts to operationalize the idea of a running tally on each of the Court's precedents. Black & Spriggs (2013) utilize Supreme Court precedent vitality, and define it in the following way: "A one-year lag of the total number times a precedent has been positively interpreted by the Supreme Court minus the number of times it has been negatively interpreted."

In creating a precedent treatment differential, vitality relates precedent treatments directly. As vitality would increase from zero, the indication from the Supreme Court would be that the precedent is valued or more vital. Higher values of vitality signal the circuit court that the justices would prefer positive treatment (indicating an effect on the circuit's treatment itself). Conversely, lower values of vitality signal that the precedent has generally been narrowed in its applications. In connecting vitality with opinion complexity, when the circuit opts to go against the vitality signals from the Supreme Court, we would expect opinion complexity to increase in order for the circuit panel to justify the use of the precedent against the Supreme Court's preferences and to insulate against potential review.

As a result of this argument, I constructed two precedent vitality measures. First, Supreme Court precedent vitality is measured as the number of prior positive treatments by the Supreme Court minus the number of negative treatments by the Supreme Court. Second, lower court precedent vitality is identical to the Supreme Court measure, except the prior treatment count are from within the circuit adjudicating the instant case. The empirical results are presents in Table 8 below.[7]

Across all three columns of Table 8, the explanatory variables of interest are in the substantively appropriate direction and are statistically reliable. These results are largely comparable to those in Column 1 of Table 2 in the main manuscript, which are also available in Column 1 of Table 7 in this document. Unfortunately, neither precedent vitality measure – *Supreme Court Precedent Vitality* and *Circuit Court Precedent Vitality* – achieve statistical significance. Interestingly, I estimated additional models excluding neutral treatment circuit cases, and while the vitality measures improve, they do not approach statistical significance (Supreme Court Precedent Vitality: $t = 1.08$, Circuit Court Precedent Vitality: $t = 0.70$). Indeed, even if the variables did achieve statistical significance, the results would be something of a conundrum, since higher levels of vitality (both Supreme Court and Circuit Court, in the omitting neutral models) lead to increases in opinion complexity. Likewise, utilizing just the Supreme Court's positive treatment count or negative treatment count in the models also leads to higher levels of opinion complexity.

10.7 *Shepard's* Treatment Categories

In the main manuscript, the main focus was on negative, neutral and positive treatment. I relied heavily on the Westerland et al. (2010) coding scheme. To my knowledge, they followed – in large part – the coding norms of other precedent studies, including those provided by Hansford & Spriggs (2006). Surely, much of any potential controversy that arises with the categorization stems from the negative interpretation components. Positive treatment requires little to no debate, since it contains only one of the *Shepard's* treatments: "comply." Much the same, neutral only contains "explained" and "harmonized" treatments. Still, some have called neutral treatments "soft positives," since the treatment goes beyond a mere string citation and it does not distinguish the instant case's facts from the precedent (e.g. Hinkle 2015).

[7] I also estimated models with interaction terms between the vitality measures and negative treatment. The results for the vitality measures and the interaction term were objectively worse, while all three explanatory variables of interest (negative treatment, distance from Supreme Court to precedent, and their interaction) attained statistical and substantive significance. Furthermore, I estimated models with the vitality measures, negative treatment, and their interaction, and the models performed quite poorly.

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Table 8: Random Effects Multilevel Regression Estimations of Opinion Complexity Using Precedent Vitality

	Outcome Variable: Complexity of Court Opinion		
	(1)	(2)	(3)
Distance from Supreme Court to Precedent	1.460*	1.450*	1.464*
	(0.440)	(0.439)	(0.440)
Negative Treatment	0.393*	0.394*	0.393*
	(0.164)	(0.164)	(0.164)
Negative Treatment	−1.488*	−1.491*	−1.492*
× Distance from Supreme Court to Precedent	(0.573)	(0.573)	(0.574)
Supreme Court Precedent Vitality	0.009	–	0.010
	(0.025)	–	(0.026)
Circuit Court Precedent Vitality	–	−0.001	−0.002
	–	(0.010)	(0.010)
Constant	−0.504*	−0.496*	−0.504*
	(0.137)	(0.135)	(0.137)
Random effects:			
Supreme Court Precedent	2.094	2.086	2.095
	(1.447)	(1.444)	(1.447)
Observations	9,797	9,797	9,797
Akaike Inf. Crit.	55,295.13	55,297.09	55,304.42
Bayesian Inf. Crit.	55,345.46	55,347.42	55,361.93
Note:			*p<0.05

With regard to some differences across negative treatments, Hansford & Spriggs (50 2006) notes, in line with the *Shepard's* coding manual, a distinction between "strong" and "weak" negative interpretation, where the latter is – as you suggest – the "distinguish" category: "Distinguish may at times represent a somewhat weaker form of negative interpretation than the others, because, while at a minimum it indicates that a case is inapplicable, it may not necessarily restrict the application of the precedent." Hansford & Spriggs (2006) go on to examine the reliability and validity of both the positive and negative interpretation categories, and find evidence in support of their coding.

I received the original *Shepard's* precedent coding from Westerland et al. (2010). Using these data, I have estimated two new models using a different explanatory variable for Negative Treatment, with considerations for more distinctly negative treatments (beyond "distinguished"): "conflicting," "criticized," "limited," "questioned," or "overruled." The problem that arose out of the original, full dataset was this: almost all of the treatments fall into one of three categories: "distinguished," "explained," or "followed." In Table 9 below, I provide the tabulation of the data. Please note that due to some duplicates in the original Westerland et al. (2010) data, the total n do not match across the dataset. The overall number of duplicates in the full precedent data is 204.[8]

Given the extreme nature of the distribution across the categories, I was skeptical that a new models with different negative precedent interpretations would reveal anything; it appears there is just too little variation in the data. Still, I present two new models in Table 10, and, surprisingly, I do find some interesting results. The data in Table 10 are only for those negative treatment cases ($n = 2,939$ in the original data). The *Strong Negative Treatment* variable is equal to zero for distinguished treatment, and equal to 1 for any other, stronger negative treatment: conflicting, criticized, limited, overruled, questioned.

In the OLS model in Column 1 of Table 10, we see the interaction coefficient achieves statistical significance, which suggests – given the presence of a strong negative precedent treatment

[8] Some notes about the coding of the Westerland et al. (2010) coded precedent treatments. Total n in the replication data: 9,797. Total n in the precedent coding data: 10,001. Several of the coding categories had labels, which I normalized: "critic st," "followed\+M59," "overrule st." These may have been important notes in the original coding, but I normalized them based on my understanding of the *Shepard's* coding scheme.

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Table 9: Tabulation of the *Shepard's* Treatment Data

Shepard's Treatment		Umbrella Category	
Conflicting	2		
Critical	4		
Criticized	33		
Distinguish	2,753	Negative	2,939
Explained	2,052	Neutral	2,139
Followed	4,909	Positive	4,923
Harmonized	122		
Interpret	1		
Limited	12		
Not Follow	11		
Overruled	6		
Parallel	4		
Questioned	91		
Superseded	1		
Total	10,001		9,797

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Table 10: OLS & Random Effects Estimations of Opinion Complexity Using Negative Precedent Interpretations

	Outcome Variable: Complexity of Court Opinion	
	OLS	*Random Effects*
	(1)	(2)
Strong Negative Treatment†	1.078	1.319^{*}
	(0.595)	(0.631)
Distance from Supreme Court to Precedent	−0.160	−0.145
	(0.477)	(0.581)
Strong Negative Treatment	-3.035^{*}	−2.453
Distance from Supreme Court to Precedent	(1.549)	(1.848)
Constant	0.026	−0.007
	(0.136)	(0.179)
Random effects:		
Supreme Court Precedent	–	2.199
	–	(1.483)
Observations	2,901	2,901
Akaike Inf. Crit.	16,376.78	16,233.75
Bayesian Inf. Crit.	16,406.64	16,269.58

Note: $^{*}p<0.05$; †: Strong Negative: conflicting, criticized, limited, overruled, questioned

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in the case, and as the Supreme Court increasingly dislikes the precedent – decreasing opinion complexity, compared to cases with distinguished precedent treatment. How we are to interpret that result is less clear; stronger negative precedent treatments result in less linguistic complexity when the Supreme Court increasingly dislikes the precedent. In other words, it might seem that distinguishing treatment requires additional opinion complexity, even given variations in the Supreme Court median's precedent preferences. In a sense, this result is consistent with the findings in the main manuscript, as it suggests increasingly strong negative treatment requires less complexity when the Supreme Court increasingly dislikes the precedent.

Column 2 of Table 10 reveals another interesting result, where we see the conditional marginal effect for *Strong Negative Treatment* is positive and statistically reliable. This suggests, when the median justice highly prefers the Court's precedent (i.e. Distance from Supreme Court to Precedent equals 0), and the circuit treats that precedent with strong negative treatment, the circuit judge uses increasingly complex opinion language. This result has as its reference category distinguished treatment, suggesting that when the circuit judge distinguishes a precedent highly preferred by the Supreme Court, the judge uses less complex language than if the judge treated the precedent more strongly.

I hesitate to put too much stock in these results given the extremely small number of strong negative treatment cases present in the data. Even more, I would not go further to examine these strong negative treatment cases within the context of the full data (i.e. including positive and neutral treatment) since the variation would be diminished even further. Still, the results in Table 10 are encouraging insofar as they are in line with my broader expectations.

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10.8 Descriptive Statistics

Table 11: Summary Statistics for Opinion Data

Variable	*Mean*	*StdDev.*	*Min*	*Max*
Complexity of Court Opinion	0	4.214	-21.664	17.516
(1) Cause	1.801	0.560	0	5.08
(2) Certain	1.069	.348	0	3.38
(3) Differentiation	2.759	0.625	0	6.82
(4) Discrepancies	0.940	0.349	0	3.34
(5) Insight	2.621	0.863	0	7.18
(6) Negations	1.278	0.319	0	3.880
(7) Tentativeness	1.840	0.523	0.32	6.02
Precedent Treatment:	*Freq.*		*Percent*	
Negative Treatment (=1)	2.861		29.20	
Neutral Treatment (=0)	2,115		21.59	
Positive Treatment (=0)	4,821		49.21	
Ideological Distance Measures:	*Mean*	*StdDev.*	*Min*	*Max*
Distance from Supreme Court to Precedent	0.226	0.161	0	0.841
Distance from Panel to Precedent	0.304	0.221	0.000	1.246
Distance from Supreme Court to Panel	0.243	0.162	0.000	0.861

References

Black, R. C., & Spriggs, J. F. (2013). The citation and depreciation of us supreme court precedent. *Journal of Empirical Legal Studies*, *10*(2), 325–358.

Bodner, T. E. (2008). What improves with increased missing data imputations? *Structural Equation Modeling*, *15*(4), 651–675.

Hansford, T. G., & Spriggs, J. F. (2006). *The politics of precedent on the US Supreme Court*. Princeton University Press.

Hinkle, R. K. (2015). Legal constraint in the us courts of appeals. *The Journal of Politics*, *77*(3), 721–735.

Johnson, C. A. (1987). Law, politics, and judicial decision making: Lower federal court uses of supreme court decisions. *Law and Society Review*, 325–340.

Lindquist, S. A., Martinek, W. L., & Hettinger, V. A. (2007). Splitting the difference: Modeling appellate court decisions with mixed outcomes. *Law & Society Review*, *41*(2), 429–456.

Moyer, L. P. (2012). The role of case complexity in judicial decision making. *Law & Policy*, *34*(3), 291–312.

Owens, R. J., & Wedeking, J. (2012). Predicting drift on politically insulated institutions: A study of ideological drift on the United States Supreme Court. *The Journal of Politics*, *74*(02), 487–500.

Owens, R. J., Wedeking, J., & Wohlfarth, P. C. (2013). How the Supreme Court alters opinion language to evade congressional review. *Journal of Law and Courts*, *1*(1), 35–59.

Songer, D. R., Kuersten, A. K., & Haire, S. B. (n.d.). *The judicial research initiative (juri) at the university of south carolina: The united states courts of appeals databases.* Retrieved from http://artsandsciences.sc.edu/poli/juri/appct.htm

Spaeth, H. J., Epstein, L., Martin, A. D., Segal, J. A., Ruger, T. J., & C, B. S. (2017). *The supreme court database, version 2017 release 01.* Retrieved from `http://Supremecourtdatabase.org`

Westerland, C., Segal, J. A., Epstein, L., Cameron, C. M., & Comparato, S. (2010). Strategic defiance and compliance in the US Courts of Appeals. *American Journal of Political Science*, *54*(4), 891–905.