Supplementary Information

Presidential Negative Partisanship

Contents

A Construction of the Corpus and Measures

A.1 Corpus Construction

To create my corpus of presidential speeches, I scrape documents on the American Presidency Project Website, hosted by UC Santa Barbara (Woolley and Peters N.d.) at `https://www.presidency.ucsb.edu/`. The collection of this corpus proceeded in waves. In the first wave, I collected all speeches tagged as `Spoken Addresses and Remarks` and `Miscellaneous Remarks`. In subsequent collection waves, these categories had been combined into a single `Spoken Addresses and Remarks` category, which I collected. In addition to adding new documents, the authors of the project may update the site, recategorize documents, and change attributes. As such, the data I collected may include or exclude documents that the webhosts changed after my initial collection efforts.

In the final corpus, I exclude speeches given before the president's first day in office, those given during their lame duck period or after, and eulogies. For presidents who die in office, I exclude speeches given on their final day in office which may have been prepared but not delivered.

A.2 Dependent Variable Keywords

To identify party references, I identify all speeches that contain at least one of the following keywords: `democrat`, `democrats`, or `republicans`. These words are preceded and followed by a regex word boundary character, `\b`, to avoid false positives. I also search for all of the following keywords preceded by the word `democratic` or `republican`: `party`, `ticket`, `congress`, `president`, `administration`, `leadership`, `leader`, `platform`, `governor`, `candidate`, `convention`, `senator`, `victory`, `congressman`, `senate`, `majority`, `house`, `member`, `committee`, `congressmen`, `nominee`, `side`, `caucus`, `congressional`, `controlled`, `delegation`, `issue`, `fundraiser`, `opposition`, `program`, `primary`, `votes`, `team`, `chair`, `congresses`, `chairman`, `speaker`, `national`, `and`, and `or`. These words are preceded, but not followed by, a regex word boundary character to capture plurals and possessives.

To identify references to predecessors, I search for references to the last names of the two presidents of the opposite party serving before the sitting president. To identify references to congressional leaders, I search for the last name of any individual who served as the Speaker of the House, minority floor leader, or Senate majority or minority leader during the Congress in which a speech was delivered.[1] The names of these individuals

[1] In the 79th and 80th Congresses, the Republican floor leader was Wallace H. White Jr. Here, I manually

come from Heitshusen (2019) through 2019 and were updated by the author thereafter.

A.3 GPT Method to Extract References

To instruct the GPT model to extract the relevant text, I programmatically called the OpenAI API `GPT-4o-mini` model and fed it the below instructions. To focus the model on the references, I replaced each out-party reference in the text with a unique placeholder that begins with 'zzoutref_', ensuring it would not be confused for any other piece of text. After the model extracted relevant portions, they were returned as a column of a data frame. The named entities were not replaced before conducting sentiment analysis. This biases sentiment up on average.

> Given the following text from political speeches, extract the parts that are directly relevant to or describe the entity represented by 'zzoutref' (with trailing text and numbers you can ignore e.g., zzoutref_pres10). The entity described by 'zzoutref' is always the opposition political party or a member of the opposition party. You can use this information to inform your judgment of what should or should not be included.
>
> Note that the extracted text will be used to perform sentiment analysis with the goal of predicting the speaker's stance toward 'zzoutref'. It is crucial to extract all parts of the text directly relevant to 'zzoutref' and the surrounding context to accurately assess the speaker's view. However, balance is key: include enough context to determine stance without including irrelevant content that might skew the sentiment analysis. It is also very important to note that many statements may compare and contrast 'zzoutref' with the speaker or another group. The pieces relevant to our understanding of the stance toward 'zzoutref' should be captured, but be very careful not to include the parts of the statement where the speaker is speaking about themselves or another group, even if it means breaking the sentence when you return extracted text.
>
> Follow these guidelines strictly:
>
> 1. **High Relevance (Always Include):**

screen each speech that references "White" to ensure I don't capture false positives like White House.

- Text that directly mentions ’zzoutref’. You must **always** include the ’zzoutref’ reference in your extracted text.
- Text that clearly refers to the same entity using pronouns (they, them) or descriptive phrases (these people, the opposition) immediately before or after a mention of ’zzoutref’.
- If a reference to ’zzoutref’ spans multiple sentences, include all relevant text that forms part of that reference.

2. **Medium Relevance (Include if directly connected):**

   - Text that provides important context about the actions, characteristics, or impact of ’zzoutref’, even if ’zzoutref’ is not directly mentioned.
   - Text that describes party or partisan politics as these may be relevant to our understanding of how ’zzoutref’ should be thought of (perhaps in a positive, bipartisan manner or a negative partisan manner).
   - Text that describes ongoing debates or lawmaking if it is relevant to our understanding of ’zzoutref’ either negatively (e.g., opposition, obstruction, delay) or positively (e.g., bipartisanship, compromise, cooperation).
   - Only include these if they are clearly about the same topic and do not represent deviations from ’zzoutref’.
   - Comparative statements that describe ’zzoutref’ in relation to others, but **do not** include parts that are referring to the speaker or others.

3. **Low Relevance (Do Not Include):**

   - Sentences that introduce new topics or subjects not directly related to ’zzoutref’.
   - Personal anecdotes or tangential information that doesn’t directly characterize or impact ’zzoutref’.

4. **General Instructions:**

   - If there are multiple ’zzoutref’ mentions, consider them as referring to the same entity or group.
   - Maintain the original wording and order of the extracted text. **Do not** create any new content. Only maintain subsets of the original content.

Include the trailing numbers when you return the ′zzoutref′ reference (e.g., return ′zzoutref_13′ **not** ′zzoutref′) as it is important for internal tracking.

- Return the extracted text as a single, continuous string without any additional commentary or modifications.
- If in doubt about the relevance of a sentence, err on the side of exclusion.

Before returning the results, carefully analyze each sentence:

1. Identify the main subject of each sentence.
2. Determine if and how it relates to ′zzoutref′.
3. Assess its importance for understanding the speaker′s stance toward ′zzoutref′.
4. If it′s a comparative statement, include only the part that is directly relevant to ′zzoutref′.
5. You may need to break up sentences and return fragments depending on the context and nature of the text. You may also need to merge sentences or phrases that are not naturally connected if the intervening text is not relevant to ′zzoutref′.
6. Decide whether to include it based on the relevance guidelines above.

Remember, no matter what, you must **always** include the ′zzoutref′ reference in your extracted text. Ignore any parts of the text that are not directly related to ′zzoutref′ or crucial for understanding the speaker′s stance toward ′zzoutref′.

Below are some examples with commentary to inform your decision-making:

Original Text 1: ″I′d like to add a comment about a very important matter as well. It′s ironic that on a day when we are making an announcement like this, I again have the responsibility to set the record straight because of false allegations made by the zzoutref_pres10 nominee for President, Governor Reagan.″

You should extract: ″It′s ironic that on a day when we are making an announcement like this, I again have the responsibility to set the record straight because of false allegations made by the zzoutref_pres10 nominee for President, Governor Reagan."

Comments: The point about "adding a comment" is not relevant to the reference and should be excluded.

Original Text 2: "I want every American, every Member of Congress, every State official, everybody who works for a mayor or a city government to join me in putting this strategy to work. This is a national strategy, not a Federal strategy. I don't want it to become partisan in any way, shape, or form. This should unite us in America: people in the private sector, people in Government, people at the local level, people at the national level, zzinref and zzoutref_rep145, people who are inside this institution, and people who are beyond its walls. We have a common interest in saving our country. And all of us have a personal responsibility to pursue. This drug strategy we announce today is our attempt to be your partner and pursue our personal responsibility. And together, together we can do it."

You should extract: "I don't want it to become partisan in any way, shape, or form. This should unite us in America: people in the private sector, people in Government, people at the local level, people at the national level, zzinref and zzoutref_rep145, people who are inside this institution, and people who are beyond its walls. We have a common interest in saving our country. And together, together we can do it."

Comment: Here, some of the text preceding the reference is relevant to understanding the fact that the speaker wants zzoutref to work with them for the common good. Note too that some of the later text is excluded but the last point about working together is included because it helps us understand the context of what 'zzoutref_rep145' should do.

Original Text 3: "The zzoutref_rep14 Party should work with the zzinref Party to get rid of this. It is a bad precedent. We're spending more and more money on interest on the debt. It we don't balance the budget next year, we'll spend more on interest than we do on defense. This year, the budget would be in balance but for the interest we pay on the debt run up in the 12 years before I took office. And we've taken the deficit from $290 billion to $160 billion a year, and we ought to go all the way until we get the job done. America should invest in the future, not squander the present. And we should all be for that."

You should extract: "The zzoutref_rep14 Party should work with the zzinref Party to get rid of this. It is a bad precedent. We're spending more and more money on interest on the debt. It we don't balance the budget next year, we'll spend more on interest than we do on defense. This year, the budget would be in balance but for the interest we pay on the debt run up in the 12 years before I took office. And we've taken the deficit from $290 billion to $160 billion a year, and we ought to go all the way until we get the job done. America should invest in the future, not squander the present. And we should all be for that."

Comment: This is a tricky one! Here the entire paragraph is relevant for understanding why the speaker wants zzoutref_rep14 to work with them.

Original Text 4: "The zzoutref_lead1 talk tough, the liberal zzoutref_pres2, about crime. But let me tell you something: The other day I had a visit in the Oval Office from eight individuals, grassroots family men, all coming up there. They said, 'We are for you for President,' and they represented the Fraternal Order of Police of Little Rock, Arkansas. I was proud to have their support."

You should extract: "The zzoutref_lead1 talk tough, the liberal zzoutref_pres2, about crime."

Comments: This one is straightforward. After the speaker references zzoutref_lead1 and zzoutref_pres2, they move on to other irrelevant anecdotes.

Original Text 5: "Mr. Chairman, Commander Burdine, the zzoutref_dem4 Senator from Maine, distinguished guests, my fellow veterans and friends:"

You should extract: "the zzoutref_dem4 Senator from Maine"

Comments: This is a list of individuals so the additional information in the paragraph is not connected to the 'zzoutref_dem4'. Note that here you need to break up the sentence to return the relevant context.

Original Text 6: "At the end of the war the zzoutref_pres2 said we couldn't provide 60 million jobs. But we did it. We now have over 62 million people employed in this great country."

You should extract: "At the end of the war the zzoutref_pres2 said we couldn't provide 60 million jobs."

Comments: The speaker says this and then begins talking about their own achievements. The rest should not be included because it would make the sentiment positive when the reference to 'zzoutref_pres2' is negative.

Original Text 7: "When it comes to detaining terrorists, what's the zzoutref_dem26 answer?"

You should extract: "what's the zzoutref_dem26 answer"

Comments: This one is tricky! Here, the reference to terrorists is topical but not relevant to the 'zzoutref_dem26' reference. The relevant part is their answer, but that doesn't necessarily depend on the topic. The speaker could have just as easily have said "When it comes to lowering the debt," and so because it is a generic lead-in, it should not be captured.

Original Text 8: "This work has nothing to do with partisan politics—nothing at all. A great many of you are zzoutref_rep117, a good many are Democrats; quite a number do not belong regularly to one party or the other. We are not the least bit interested in the partisan side of this picture."

You should extract: "This work has nothing to do with partisan politics—nothing at all. A great many of you are zzoutref_rep117, a good many are Democrats; quite a number do not belong regularly to one party or the other."

Comments: Although the first sentence is not a direct reference to 'zzoutref_rep117', the speaker mentioning partisan politics is relevant to our understanding of how they think about ’zzoutref_rep117’.

Text: {text}

Extracted relevant text:

A.4 Sentiment Accuracy

To assess accuracy, I randomly sampled 230 paragraphs that referenced the opposition party. I coded statements as negative, neutral, or positive blind to their machine-labeled score. I then trichotomized the machine-labled, continuous measure into terciles where those below 0.33 were coded as negative, at or above 0.66 as positive, and in between as neutral. Below are the confusion matrices for the GPT-extracted paragraphs (accuracy of 0.66) and full paragraphs (accuracy of 0.60). Both accuracy scores well exceed the 0.33 accuracy of a random guess and defaulting to negative, 0.44.

Table A1: Confusion Matrices for GPT-Extracted Paragraphs (Top) and Full Text (Bottom)

	Machine Labeled		
Hand-Coded	Negative	Neutral	Positive
Negative	66	23	12
Neutral	11	37	9
Positive	3	21	48

	Machine Labeled		
Hand-Coded	Negative	Neutral	Positive
Negative	59	24	18
Neutral	16	27	14
Positive	3	16	53

B Additional Empirical Results

B.1 Regression Results for Sentiment Analysis

In Table B1, I present regression results for a series of models examining paragraph-level sentiment. Column 1 is the baseline, interacting the number of out-party references per 1,000 words with the variables from Table 3, column 1 in the main text. The interaction terms show that an increase in presidents referencing the opposition is associated with more negative sentiment for presidents who experienced congressional competition and who served during divided government. Although speech is more negative during major elections, references themselves do not become more negative. These results generally hold across the remaining specifications.

In column 2, I use the fixed effects specification similar to Table 3, column 2. In column 3, I replicate the results in column 2 using sentiment computed on the entire paragraph rather than the GPT-extracted snippet. The results are quite similar. In column 4, I re-specify references as only references to the opposition party (not leaders or presidents). Here, major elections is positive and statistically significant. The instability of the coefficient on major elections likely reflects the fact that during elections, presidents often evoke opposition *voters* in a positive light but elected officials negatively. In column 5, I run a model similar to that in column 1 to assess whether these results hold for the Truman Period and Modern Period separately. Here, the interaction effects are both negative as expected: more references in both periods are associated with more negative rhetoric. To interpret these differences more practically, I use this model to generate the marginal effect of each competitive time period (vs the baseline), setting the number of references per 1,000 words to 0 and 1. Then I compute the differences in these marginal effects within time periods. I conduct 500 bootstraps to compute confidence intervals. Ultimately, I find that a 1 reference increase per 1,000 words in the Truman Period (as compared to the non-competitive periods) is -0.0012 $[-0.0022, -0.0003]$.A 1 reference increase per 1,000 words in the Modern Period (as compared to the non-competitive periods) is -0.0038 $[-0.0045, -0.0030]$. In both periods, an additional out-party reference (per 1,000 words) is associated with more negative speech, as compared to the same increase during the non-competitive periods.

Table B1: Regression Results for Sentiment Models

	(1)	(2)	(3)	(4)	(5)
Out-Party Ref. per 1,000 Words	−0.002***	−0.005***	−0.004***		−0.002***
	(0.000)	(0.000)	(0.000)		(0.000)
Party Refs. Only				−0.006***	
				(0.000)	
Majority Competition (80–84th, 97–118th)	0.009***				
	(0.002)				
Out-Party Ref. x Majority Competition	−0.003***				
	(0.000)				
Divided Government	0.004+	0.006*	0.005*	0.005+	−0.001
	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)
Out-Party Ref. x Divided Government	−0.001*	−0.001***	−0.001**		−0.001*
	(0.000)	(0.000)	(0.000)		(0.000)
Major Election Season	−0.022***	−0.022***	−0.021***	−0.023***	−0.022***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Out-Party Ref. x Major Election	0.000	0.000	0.000		0.000
	(0.000)	(0.000)	(0.000)		(0.000)
Party Refs. Only x Divided Government				−0.001*	
				(0.000)	
Party Refs. Only x Major Elections				0.001**	
				(0.001)	
Truman Period (80th–84th)					−0.065***
					(0.004)
Modern Period (97th–118th)					0.022***
					(0.002)
Out-Party Ref. per 1,000 Words x Truman Period					−0.001*
					(0.000)
Out-Party Ref. per 1,000 Words x Modern Period					−0.004***
					(0.000)
Republican	0.017***				0.015***
	(0.002)				(0.002)
Presidential Approval	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Major War	−0.028***	−0.016***	−0.016***	−0.015***	−0.014***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
First 100 Days	0.009+	0.007	0.007	0.006	0.005
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Term	0.002	0.010***	0.011***	0.011***	0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Fixed Effects					
President		✓	✓	✓	
Month	✓	✓	✓	✓	✓
Num.Obs.	734918	734918	734918	734918	734918
R2 Adj.	0.018	0.030	0.028	0.029	0.023
R2 Within Adj.	0.015	0.011	0.009	0.011	0.020

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

Notes: Coefficients are from ordinary least squares models. The dependent variable is a measure of paragraph-level sentiment where more positive (negative) values are associated with more positive (negative) rhetoric. Standard errors are clustered at the speech-level.

B.2 Reference Type Results

To what extent do these patterns differ by the type of reference presidents make (whether to the party, past presidential predecessor, or leader)? Before diving into the results, I note that party references compromise the overwhelming majority of opposition references presidents make: 75% of all opposition references are party references, compared to 18% of past president references and 7% of opposition leader references.

In Table B2, I reanalyze my results independently for each of these three types of references. Odd columns measure frequency using the reference per 1,000 words dependent variable at the speech level. Even columns measure sentiment using the sentiment dependent variable at the paragraph level with standard errors clustered on speeches. As shown in the first row, all reference types are consistently more negative on average than non-referencing paragraphs, suggestive of an oppositional framing whether presidents target parties or people. Second, in terms of frequency, only generalized party references vary with institutional covariates as predicted by my theory. Personalized references (i.e., presidential and congressional leader references) follow more idiosyncratic patterns. However, this differential pattern does not have strong implications for my theory. Iyengar, Sood and Lelkes (2012) finds that generalized out-party animus is effective at polarizing co-partisans while Nicholson (2012) finds that leader cues are more effective at creating policy polarization. Finally, Iyengar and Krupenkin (2018) shows that out-party animus is key to mobilizing voters in the modern era. Thus, it's not clear whether one type of reference or the other is ultimately more effective at mobilizing voters. Rather, that all reference types are more negative on average, paired with the fact that party references (which comprise three-quarters of all references) follow the expected patterns, is in line with my theory of presidential negative partisanship as a base rallying, rather than legislative, strategy.

Table B2: Regression Results for Reference Type Models

	Out-Party		Out-President		Out-Leader	
	(1)	(2)	(3)	(4)	(5)	(6)
Opp. Reference		−0.006***		−0.005***		−0.002***
		(0.000)		(0.000)		(0.000)
Truman Period (80th–84th)	0.552***	−0.062***	−0.079**	−0.071***	−0.029*	−0.071***
	(0.037)	(0.004)	(0.025)	(0.004)	(0.013)	(0.004)
Modern Period (97th–118th)	0.149***	0.020***	−0.025+	0.019***	0.016*	0.019***
	(0.018)	(0.002)	(0.013)	(0.002)	(0.006)	(0.002)
Divided Government	0.100***	−0.002	−0.015	−0.002	0.006	−0.002
	(0.017)	(0.002)	(0.011)	(0.002)	(0.006)	(0.002)
Major Election Season	0.524***	−0.021***	−0.007	−0.025***	0.011	−0.025***
	(0.029)	(0.003)	(0.020)	(0.003)	(0.010)	(0.003)
Republican	−0.123***	0.014***	0.004	0.015***	−0.021***	0.015***
	(0.015)	(0.002)	(0.011)	(0.002)	(0.005)	(0.002)
Presidential Approval	−0.010***	0.001***	−0.002***	0.001***	−0.001**	0.001***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Major War	0.008	−0.013***	0.046**	−0.014***	0.018*	−0.014***
	(0.024)	(0.003)	(0.017)	(0.003)	(0.008)	(0.003)
First 100 Days	−0.014	0.005	0.073**	0.005	0.004	0.005
	(0.041)	(0.005)	(0.028)	(0.005)	(0.014)	(0.005)
Term	−0.062***	0.004+	−0.071***	0.003+	−0.015**	0.004+
	(0.015)	(0.002)	(0.011)	(0.002)	(0.005)	(0.002)
Month Fixed Effects	✓	✓	✓	✓	✓	✓
Num.Obs.	26954	734918	26954	734918	26954	734918
R2 Adj.	0.054	0.021	0.004	0.014	0.002	0.013
R2 Within Adj.	0.035	0.018	0.004	0.011	0.001	0.010

Notes: Coefficients are from ordinary least squares models. The dependent variable in columns 1, 3, and 5 is the number of out-party references per 1,000 words in a speech. The dependent variable in columns 2, 4, and 6 is a measure of paragraph-level sentiment where more positive (negative) values are associated with more positive (negative) rhetoric. Standard errors are clustered at the speech-level.

B.3 Obama Case Study

In 2008, when Barack Obama won the presidential election, Democrats retained control of both chambers of Congress—increasing their margins to 257 House seats and 58 effective seats in the Senate (56 Democrats and 2 Independents caucusing with Democrats). However, the contest between Al Franken (D) and Norm Coleman (R) for Minnesota's seat was too close to call. Although Franken led, Coleman challenged the result, leading to a lengthy court battle. During this period, Arlen Specter (R-PA) unexpectedly switched parties on April 28, 2009. Franken was then declared the victor on June 30, 2009, officially giving Democrats their 60-seat super-majority, allowing them to unilaterally overcome any Republican filibuster.

During the 2009 session, President Obama and Democrats focused on developing and passing what would become the Affordable Care Act. Although the president was not naive, recognizing that the opposition had strategic incentives to oppose the package, he did engage in good faith negotiation with the few key Republicans—despite his super-majority. As summer wore on, however, the president saw that these effort were failing, writing in his memoir that, [Senator Max Baucus's] optimism that he could produce a bipartisan bill began to look delusional." (Obama 2020). Further complications followed. On August 25, 2009, Senator Ted Kennedy (D-MA) passed away. A new democratic senator was appointed to take his place, and a special election was scheduled for January 19, 2010. During this brief period of Democratic control, the party passed the Affordable Care Act through the House and Senate with no Republican support. As lawmakers returned from Christmas break, they needed to reconcile the two versions of the bill by passing the same legislation through both chambers. Ultimately, this effort would be stymied by Scott Brown's (R-MA) unexpected victory in the special election on January 19, 2010. With only 59 Senators, Democrats could no longer unilaterally overcome a Republican filibuster.

The president could have given up, tried to restart the process with more Republican input (however unlikely), or tried other procedural tactics to pass the legislation without Republican support. The president chose the latter, using the reconciliation process to pass the bill through the Senate with a simple majority. As this process played out, the president attacked Republicans rather than trying to engage them in good faith. He held two televised events in which he took questions from Republicans about the bill and listened to their proposals. Although these events may have had the veneer of bipartisanship, in his memoir, the president noted, "it was clear throughout both sessions that nothing I said was going to have the slightest impact on Republican behavior...What mattered was how the two events served to reinvigorate House Democrats, reminding them that we were on the right side of the healthcare issue" (Obama 2020, 463). Rather than work with the opposition, the president tried to rally co-partisans through these public events. He also spent his time talking to hesitant Democratic lawmakers, arguing that "a 'no' vote was more likely to turn off Democrats than it was to win over Republicans and independents" (Obama 2020, 465). Ultimately, the challenge of legislating only encouraged the president to work harder to marshal his own side rather than reach out to the opposition—in contrast to his more bipartisan efforts when his party held 60 seats.

In Table B3, I present results for the relationship between President Obama's filibuster-proof Senate super-majority and the number and sentiment of references to Republicans.

Table B3: Obama's Filibuster Proof Majority and Number, Sentiment of Opposition References

	DV: Party References	DV: Sentiment
	(1)	(2)
After Super-Majority	0.536***	−0.048**
	(0.146)	(0.018)
Before Super-Majority	−0.013	0.050
	(0.225)	(0.031)
Out-Party Ref. per 1,000 Words		−0.002
		(0.002)
Out-Party Ref. x After Super-Majority		−0.005**
		(0.002)
Out-Party Ref. x Before Super-Majority		−0.001
		(0.003)
Major Election Season	0.443**	−0.077***
	(0.141)	(0.013)
Presidential Approval	−0.004	−0.007**
	(0.017)	(0.002)
First 100 Days	0.051	0.011
	(0.159)	(0.021)
Intercept	0.449	1.004***
	(0.927)	(0.117)
Num.Obs.	968	26,077
R2 Adj.	0.075	0.018

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

Note: Coefficients are from ordinary least squares models. In column 1, the dependent variable is the number of references to Republicans per 1,000 words in a presidential speech. The dependent variable in column 2 is a measure of paragraph-level sentiment where more positive (negative) values are associated with more positive (negative) rhetoric. In this model, standard errors are clustered at the speech-level.

C Exploratory Analyses

C.1 Speech Type Results

In Figure 4, I provide descriptive evidence that opposition references are more prevalent in campaign rallies than in major address or in other types of speeches (e.g., minor remarks). To determine whether these differences are significant, I regress the number of opposition references on a categorical speech-type variable where the baseline category is a major address (e.g., State of the Union Address, televised policy speech). In Table C1, both models (one without and one with president fixed effects) show that rallies contain more than one additional opposition reference per 1,000 words relative to major addresses. These results are consistent with an electoral, rather than legislative, strategy.

Table C1: Relationship Between Presidential Negative Partisanship and Speech Types

	(1)	(2)
Rally	1.201***	1.107***
	(0.076)	(0.076)
Other Speech Types	−0.476***	−0.501***
	(0.033)	(0.033)
Majority Competition (80–84th, 97–118th)	0.137***	
	(0.024)	
Divided Government	0.079***	0.219***
	(0.021)	(0.027)
Major Election Season	0.382***	0.417***
	(0.038)	(0.038)
Republican	−0.164***	
	(0.020)	
Presidential Approval	−0.014***	−0.007***
	(0.001)	(0.001)
Major War	0.138***	0.029
	(0.031)	(0.041)
First 100 Days	0.054	0.070
	(0.053)	(0.053)
Term	−0.175***	−0.068**
	(0.020)	(0.024)
Fixed Effects		
President		✓
Month	✓	✓
Num.Obs.	26954	26954
R2 Adj.	0.062	0.080
R2 Within Adj.	0.049	0.038

Note: Coefficients are from ordinary least squares models where the dependent variable is the number of references to the presidential out-party per 1,000 words in a presidential speech.

C.2 Issue Ownership Results

To determine whether presidents use more negative partisan rhetoric on owned issues during divided government, I first associate major topics with parties where appropriate following Table 3.2 of Egan (2013). Democratic topics include education, energy, health, jobs, poverty, and social security. Republican topics include crime, deficit, economy, foreign affairs, military, taxes, and trade. The remaining topics are not associated with a party. Then, I regress the number of opposition references per 1,000 words on the interaction between divided government and a binary indicator for whether a president's party owns that issue. I run two specifications, one with topic fixed effects (to account for potential baseline differences in negative partisanship across topics) and another with president fixed effects. These cannot be leveraged in the same model as issue ownership is invariant within presidents. The interaction term is positive and statistically significant in both models and the marginal effect of divided government is positive and statistically significant (model 1: 0.11 [0.05, 0.17], model 2: 0.28 [0.19, 0.37]).

Table C2: Relationship Between Presidential Negative Partisanship, Issue Ownership, and Divided Government

	(1)	(2)
Owned Issue	−0.061*	−0.332***
	(0.028)	(0.029)
Owned Issue x Divided Government	0.085**	0.100**
	(0.032)	(0.036)
Majority Competition (80–84th, 97–118th)	0.353***	
	(0.026)	
Divided Government	0.025	0.177**
	(0.035)	(0.065)
Major Election Season	0.454***	0.744***
	(0.065)	(0.078)
Republican	−0.150***	
	(0.031)	
Presidential Approval	−0.020***	−0.014***
	(0.001)	(0.001)
Major War	0.210***	0.138+
	(0.038)	(0.083)
First 100 Days	0.085	0.167**
	(0.056)	(0.060)
Term	−0.201***	0.004
	(0.024)	(0.040)
Fixed Effects		
Topic	✓	
President		✓
Month	✓	✓
Num.Obs.	725867	725867
R2 Adj.	0.094	0.017
R2 Within Adj.	0.004	0.002

Note: Coefficients are from ordinary least squares models where the dependent variable is the number of references to the presidential out-party per 1,000 words in a presidential speech.

C.3 In-Party Reference Results

In Table C3, I show that presidents generally do not engage in positive partisanship, which further supports the underlying theory of presidential negative partisanship. In model 1, presidents reference the out-party much more frequently than their own party in competitive periods and during divided government—counter to the idea that they are engaging in an equal amount of positive partisanship. Presidents reference both parties equally during election periods. In model 2, which includes presidential fixed effects, patterns are similar. Even if presidents reference their own party more under these conditions, the frequency of those references does not increase at the same rate as opposition references—indicative of the dominance of negative partisanship.

Table C3: Gap Between Out-Party and In-Party References

	(1)	(2)
Majority Competition (80–84th, 97–118th)	0.444***	
	(0.032)	
Divided Government	0.126***	0.135***
	(0.028)	(0.034)
Major Election Season	0.057	0.087+
	(0.049)	(0.049)
Republican	0.055*	
	(0.024)	
Presidential Approval	−0.011***	−0.009***
	(0.001)	(0.001)
Major War	0.180***	0.299***
	(0.042)	(0.060)
First 100 Days	0.094	0.031
	(0.063)	(0.063)
Term	−0.100***	−0.021
	(0.022)	(0.028)
Fixed Effects		
President		✓
Month	✓	✓
Num.Obs.	26954	26954
R2 Adj.	0.020	0.036
R2 Within Adj.	0.019	0.004

Note: Coefficients are from ordinary least squares models where the dependent variable is the number of references to the presidential out-party less references to the in-party per 1,000 words in a presidential speech.

In addition to the frequency results, I also attempted to measure the sentiment of in-party references following the same OpenAI and BERT pipeline. However, the accuracy of this machine coding is particularly poor. What explains the higher accuracy of out-party sentiment versus in-party sentiment? Out-party references tend to take the form of explicit attacks or clear negative compare-and-contrast statements. Presidential discussion of the opposition is generally straightforward—free from negation, irony, and implicit comparisons. As such, BERT is generally able to capture sentiment of these references accurately.

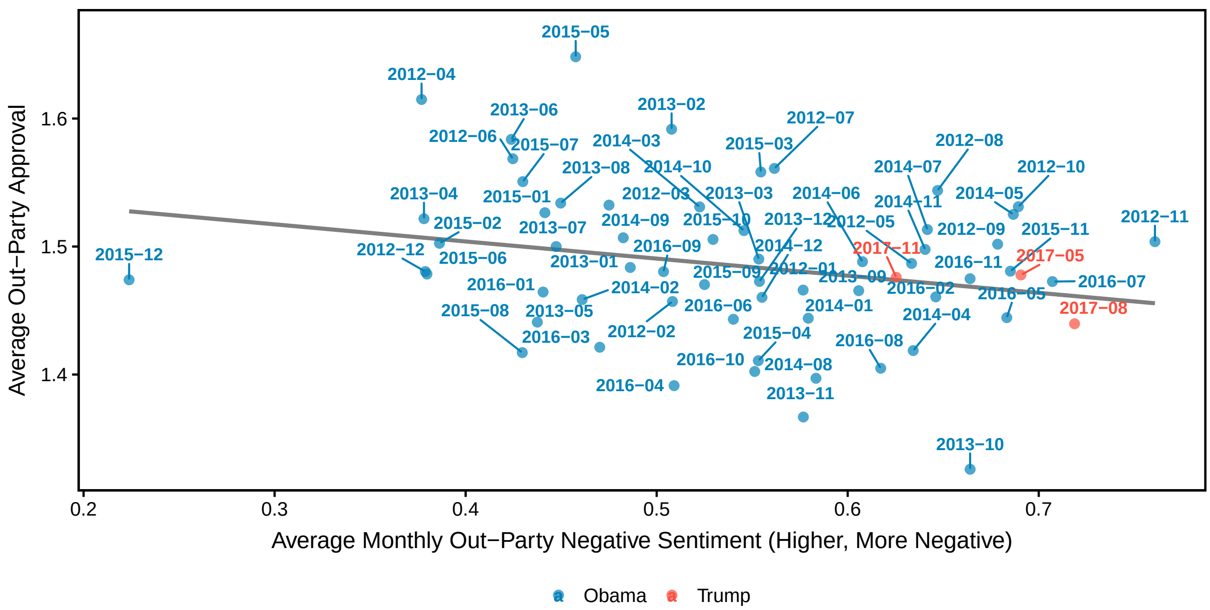
In-party references follow different patterns. In particular, they contain complex sentence constructions and make use irony, sarcasm, negation, and implicit comparisons. Presidents will discuss the terrible state of things before their party took power. Or they will highlight the negative implications of their opponents policies before saying their party disagrees. As an example, here, Ford implies that Republicans exceeded electoral expectations (positive sentiment) by criticizing pundits for their inaccurate predictions (negative sentiment): "a few months ago there were dire predictions about the fate of the republican candidates from governor down through local offices, from candidates for the united states senate, candidates for the house of representatives in the federal congress." The machine-labeled score is 0.26 (fairly negative) whereas the implied sentiment is much more positive. This type of sentence construction typifies in-party references. Given the difficulty of this task, a different approach than the one used to label out-party sentiment would be needed to accurately label the sentiment of in-party references. This would complicate interpretation of the findings without completely overhauling the sentiment coding of both types of references.

Here, I rely on the findings from the frequency results to conclude that presidents seemingly engage in negative, and not positive, partisanship. In almost all cases, presidents invoke the opposition significantly more often than their own party given the theorized institutional constraints. Even if the sentiment of in-party references is consistently positive, presidents clearly prioritize negative attacks on their opposition when facing legislative constraints rather than boosting their own side through positive in-party appeals. These effects are consistent with the behavioral underpinnings of presidential negative partisanship, where out-party affect drives electoral behavior and own-party affect has little bearing.

D Behavioral Results

In Figure D1, I plot the bivariate relationship between negative out-party sentiment on the x-axis and average out-party approval among the presidents' co-partisans on the y-axis. These two variables are negatively correlated as anticipated (-0.25). This plot also reveals that presidential negative partisanship is not colinear with time.

Figure D1: Effects of Presidential Negative Partisanship on Out-Party Approval



Note: Presidential negative partisanship is negatively correlated with out-party approval (-0.25). The x-axis is the average of all paragraphs referencing the opposition party in the prior month, where higher values indicate more negative sentiment. The y-axis is the average opposite-party approval rating presidential co-partisans provided to the question "Do you approve or disapprove of the way the [Democrats/Republicans in Washington] are doing their jobs?" on a 1-4 scale.

In Table D1 I provide regression results used to produce the marginal effects in Figure 6.

Table D1: Relationship Between Presidential Negative Partisanship and Party Approval

	Out-Party	In-Party
	(1)	(2)
Lagged Out-Party Sentiment (Reverse Coded)	−0.069	−0.018
	(0.057)	(0.109)
Presidential Co-partisan	0.095**	−0.119
	(0.032)	(0.091)
Lagged Sentiment x Presidential Co-Partisan	−0.070	0.073
	(0.047)	(0.137)
Lagged Non-Reference Sentiment	0.222	0.290*
	(0.157)	(0.128)
Election Season	0.008	0.040*
	(0.011)	(0.015)
Average Approval	0.001	−0.001
	(0.002)	(0.002)
Term	−0.031*	−0.098***
	(0.014)	(0.016)
Respondent Fixed Effects	✓	✓
Num.Obs.	29015	29140
R2 Adj.	0.620	0.627
R2 Within Adj.	0.003	0.010

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

Note: Coefficients are from ordinary least squares models where the dependent variable is a respondent's approval of the a party on a 4-point scale. Standard errors are clustered at the respondent and month-year level.

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