Measuring Partisanship and Representation in Online Congressional Communication

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Abstract

The rise of online communication and social media has created new ways for elected officials to communicate with their constituents, but also enabled the diffusion of polarizing partisan rhetoric. How have members of Congress responded to these opportunities? We introduce a new dataset of congressional communication spanning multiple platforms over a fourteen year time period to answer this question. Using computational text analysis tools, we classify messages on these platforms into purposive categories and scale the partisanship of each message along a continuous dimension ranging from left to right. After validating our measures, we produce two key findings. First, rhetoric by members of Congress has become more partisan and more negative as social media usage has increased. Second, we identify what we call the *social media feedback mirage*. Messages containing negativity, partisanship, and position-taking receive greater positive feedback on social media, even though experimental and observational evidence suggest voters disapprove of these types of messages. We conclude by discussing the implications for the current state of political discourse.

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Introduction

Communication between lawmakers and constituents is a crucial component of representation. In the 1970s, scholars such as Mayhew (1974) and Fenno (1978) put a spotlight on congressional communications, arguing that legislators strategically promote themselves to various constituencies for electoral and other reasons. A key insight was that many of the specific messages representatives send can be classified as accomplishing one of a few basic tasks such as promoting the legislator's personal brand, claiming credit for legislative accomplishments, or taking a stance on issues voters cared about.

Fifty years later, there has been both continuity and change in congressional communication. Members today continue to advertise, claim credit, and take positions. But the way in which they do so differs considerably from earlier decades. Unlike when Mayhew and Fenno were writing, the advent of online communication and social media mean that legislators can reach a vast audience both inside and outside of their district boundaries near instantaneously (Gainous and Wagner 2013; Russell 2021). These changes in the technological environment have been accompanied by changes in the political environment. Partisanship and polarization both inside and outside of Congress have grown considerably (McCarty 2019), possibly leading to more negativity and incivility in congressional rhetoric (Ballard et al. 2022, 2023; Costa 2021; Kaslovsky and Kistner 2024).

These developments have motivated a new wave of research investigating how legislators use social media and other online forms of communication. Much of this research either focuses on how legislators use new technology to accomplish the same core representational purposes as before (e.g., Cormack 2016; McKee, Evans, and Clark 2022; Russell 2021) or evaluates the type of language legislators use on these platforms, considering the extent to which political elites deploy polarizing or partisan rhetoric on social media (e.g., Ballard et al. 2022, 2023; Yu, Wojcieszak, and Casas 2024).

In this paper, we extend this research in two primary ways. First, we construct a multimodal dataset of congressional communication that spans almost the entire time period that social media has been widely used (2009 to 2022). The dataset includes over 5 million tweets, 2.5 million Facebook posts, and 184,000 email newsletters. Unlike data used in most existing research, the longitudinal nature of the data enables us to study how messaging by legislators has evolved as online communication and social media usage have become more common.

Second, we use computational textual analysis tools to classify both the representational purpose and partisan language within each tweet, permitting an evaluation of congressional communication strategies in aggregate rather than isolation. A set of supervised machine learning models are used to classify each tweet into six different categories based on the intended purpose of each message. Though not exhaustive, these categories allow for the classification of 74% of all tweets and Facebook posts and 77% of newsletter sentences. Similarly, a textual scaling model is used to place each message on a partisan spectrum from extremely Democratic to moderate to extremely Republican based on the language used. This dataset of consistently classified and scaled messages across members and legislative session offers a major resource for those studying congressional behavior, political communication, representation, and polarization, which we demonstrate via applications involving the evolution of partisan language in Congressional rhetoric and public approval of varying communication strategies.

The paper proceeds as follows. First, we discuss existing research on congressional communication, with a focus on recent research covering online communication. Second, we describe our data collection procedure as well as our classification and scaling methodologies. In this section we discuss a variety of ways we validate our measures, showing that they align with existing measures in expected ways. Next, we use our data to demonstrate applications made possible by our new data, evaluating how the public – both social media users and constituents – respond to the communication strategies members of Congress adopt. We then take advantage of the longitudinal nature of our data to explore trends in extreme and negative partisan rhetoric over time.

Finally, we conclude with some ideas for further research avenues to explore with the new data.

Congressional Rhetoric and Online Communication

Effective representation requires a dynamic, deliberative relationship between an elected official and those they represent in office (Burke 1774; Mansbridge 2003; Pitkin 1967). Representatives have to properly understand the interests of different constituency groups and disseminate information, while constituents must understand what their officials do while in office and where they stand on issues to ensure electoral accountability.

The literature on congressional representation has long recognized that members play an active and strategic role in communicating this sort of information for various purposes, particularly electoral success (Fenno 1978; Mayhew 1974; Yiannakis 1982). For instance, Fenno (1978) emphasizes how political representatives shape their public image to align with crucial district elements, crafting a distinct "homestyle" to cultivate the trust of their constituents. Mayhew (1974) highlights three activities in particular that members do to enhance their re-election chances: position-taking (establishing stances on political issues); credit-claiming (taking responsibility for work done to pass legislation and secure resources for their districts); and advertising (bolstering name recognition, highlighting appearances at events and mentions in the media). More recent work confirms that members of Congress continue to use similar messaging strategies in modern times (Grimmer 2013; Russell 2021).

But while the underlying purposes of communication may seem similar, the means of communication have changed dramatically. In the contemporary era, the rise of the internet and social media has transformed communication, allowing representatives to reach a wider audience than ever before. Members of Congress are no longer dependent on a "franking" privilege to directly reach those they represent, and even lowly rank-and-file legislators now have an ability to broadcast views far beyond the boundaries of their districts. Moreover, messages no longer have to pass through newspaper reporters or television anchors before reaching the public (Gainous and Wagner 2013; Russell 2021). The internet and social media allow representatives to reach constituents in a direct and unmediated way.

Researchers have begun studying how political elites use these new forms of media, although the field is still nascent. As recently as 2017, scholars were referring to online tools of campaign communication – "smartphones, Facebook, blogs, and the like" as "niche communication(s)" (Frankel and Hillygus 2017). Still, considerable progress has been made in understanding how these tools are used. We view these works as creating at least two major strands of research.

One of these major strands focuses on explaining what factors shape differential usage of social media, both in terms of the volume of social media usage as well as which types of messages (e.g., position-taking versus credit claiming) members choose to prioritize (Evans and Clark 2016; Evans, Cordova, and Sipole 2014; Hemphill, Russell, and Schöpke-Gonzalez 2021; Jungherr 2014; Russell 2018*a*, 2021; Scherpereel, Wohlgemuth, and Lievens 2018; Smith and Russell 2022; Straus et al. 2016; Tillery 2021). This work typically considers the political, institutional, demographic, sociological, and other variables that lead politicians to communicate in different ways.

One representative finding from this subset of the literature is the centrality of electoral incentives in driving member behavior. For example, members who represent districts that clearly favor their party are more likely to engage in position-taking, while those who represent districts with a greater number of opposing partisans tend to avoid the potential for disagreement and opt employ a strategy more focused on credit claiming (Russell 2021). This is illustrated more specifically by McKee, Evans, and Clark (2022), who find that those who were in safe partisans districts were more likely to discuss the 2019 scandal involving then-President Trump's phone call to Ukranian President Zelensky than those in more potentially competitive seats. While findings such as these demonstrate the electoral connection still exists in the social media age, they also reinforce important differences, such as (in the case of the Ukrainian phone call scandal) the speed at which members of Congress can jump into an unfolding public conversation.

A second major strand of research focuses on how rhetoric has evolved in response not just to the rise of social media, but also to the growing political polarization in American society. While many have studied the polarizing effects of social media usage on the mass public (for a review, see Tucker et al. 2018), others have focused more specifically on how political elites use social media in polarizing ways, via the language they use and how they discuss political issues online. Research on congressional rhetoric has considered the extent to which lawmakers deploy polarizing or extreme rhetoric (Ballard et al. 2023; Cowburn and Sältzer 2024; Kaslovsky and Kistner 2024), negative partisan attacks (Russell 2018*b*; Yu, Wojcieszak, and Casas 2024), and uncivil language (Ballard et al. 2022). Once again, a common theme in this work is the importance of electoral incentives in shaping member behaviors. Both social media users and donors (categories with some overlap) have been found to reward this type of language with engagement and dollars, respectively (Ballard et al. 2023; Yu, Wojcieszak, and Casas 2024).

While this research has improved our understanding of how representatives communicate, most of this work has been hamstrung by four key limitations. The first limitation, common to almost all of the above cited research, is a focus on short time periods, typically one or two legislative sessions.[1] Due in part to the difficulties in collecting and cleaning communication data, most research uses at most, a few years of data, which can lead to inferential issues. For instance, some studies using data from a single session (e.g., Hemphill, Russell, and Schöpke-Gonzalez 2021; Yu, Wojcieszak, and Casas 2024) find communication differences between Democrats and Republicans, which is attributed to one party being in the majority and the other in the minority. But Democrats and Republicans differ from each other in many ways (Grossmann and Hopkins 2016), making it impossible to separate partisan differences from majoritarian differences when studying just a single session's worth of data.

Besides avoiding problems such as these, longer time spans are desirable for another reason. It's unclear whether congressional communication has stayed largely constant or evolved as so-

[1]Ballard et. al. (2022; 2023) are an exception, studying tweets spanning a period from 2009 to 2020.

cial media usage and technology has changed. Particularly given the speed of developments in online communication, a major concern is the temporal validity (Munger 2023) of findings in this area. Assessing how stable conclusions are over longer periods of time requires data covering longer periods of time.

A second issue with most existing research is examining communication on a single platform alone. The audiences members speak to when posting on a social media platform like Twitter/X – where messages are seen by a heterogeneous mix of political enthusiasts, journalists, interest group members, fellow politicians, and more – look very different from the recipients of email newsletters, which are targeted more directly towards constituents.[2] Recently published research demonstrates that these different audiences matter. Members vary in terms of how much they post on Facebook versus Twitter/X (Blum, Cormack, and Shoub 2023). Furthermore, the partisanship of member speech varies by venue, and some members appear more partisan when measured using communication in one form versus another (Green et al. 2024). Other hypotheses researchers are interested in testing may be platform-specific, and demonstrating similarities or differences across platforms can provide deeper insight.

A third issue is that research has largely studied *either* the representational content *or* the partisan tone of congressional speech. While the concepts are distinct, they are not mutually exclusive. Position-taking is often inherently partisan and elites frequently use partisan rhetoric and one or more representational strategies in the same message. Being able to analyze both content and tone simultaneously allows researchers to more precisely isolate what component of messaging is having the effects they find, without worrying about confounding the impact of one dimension for the other. For these reasons, having readily accessible and easily comparable measures of both concepts (representational purpose and partisanship) enables more robust scholarship than possible when studying either in isolation.

[2] On that latter point, offices sometimes require individuals sign up for e-newsletters using a zip code, to confirm constituency residency.

The fourth issue is that the current system, where research teams individually download, clean, and prepare different versions of similar datasets is inherently wasteful, and slows the pace of scientific progress. Having a central repository of easily accessible, ready to use data allows researchers to spend their time developing and testing theories of political communication, not repeating time-consuming data work that has been done many times over. To build on this point, having a single commonly-used dataset ensures that similar cleaning and sample inclusion decisions have been made. Idiosyncratic data processing decisions – that may not be immediately obvious to readers – can be eliminated as possible explanations when differing results emerge, making comparison of results more transparent.

For these reasons, the study of communication and representation stands to benefit enormously from a single publicly available dataset with multimodal and longitudinal data, classified by representational purpose and scaled according to the partisan positioning expressed via the message. Below, we describe how we are constructing just such a dataset.

Measuring Partisanship and Representation

To address these limitations and advance future research, we have created the *Scaled and Classified Congressional Communication (SCCC) dataset*, a new multimodal dataset spanning the years 2009 to 2022. The dataset includes posts on the two most-used social media platforms by members of Congress, Twitter/X and Facebook, as well as email newsletters, a common form of communication members use to address (primarily) constituents. In addition to the texts of these communications, we possess auxiliary variables such as Twitter/X engagement metrics (likes, retweets, etc.), as well as our partisanship and representation measurement variables.

Our measurement schemata is shown below in Figure 1, along with example messages that correspond to each category or scale position. The representational categories come directly from Mayhew (1974), although these or similar categories have been studied frequently by others (e.g., Grimmer 2013; Russell 2021; Yiannakis 1982). These categories are *Advertising* ("any effort to disseminate one's name among constituents in such a fashion as to create a favorable image"), *Credit Claiming* ("generat[ing] a belief…that one is personally responsible for causing the government, or some unit thereof, to do something that the actor…considers desirable"), and *Position Taking* ("a judgmental statement on anything likely to be of interest to political actors"). We further subdivide the credit claiming category to encompass two different forms of credit claiming, *Credit Claiming for Constituency Work* (a message taking responsibility for particularized benefits provided to constituents, the district, or the state) and *Credit Claiming for Policy Work* (a message taking responsibility for non-constituency-specific policy accomplishments).

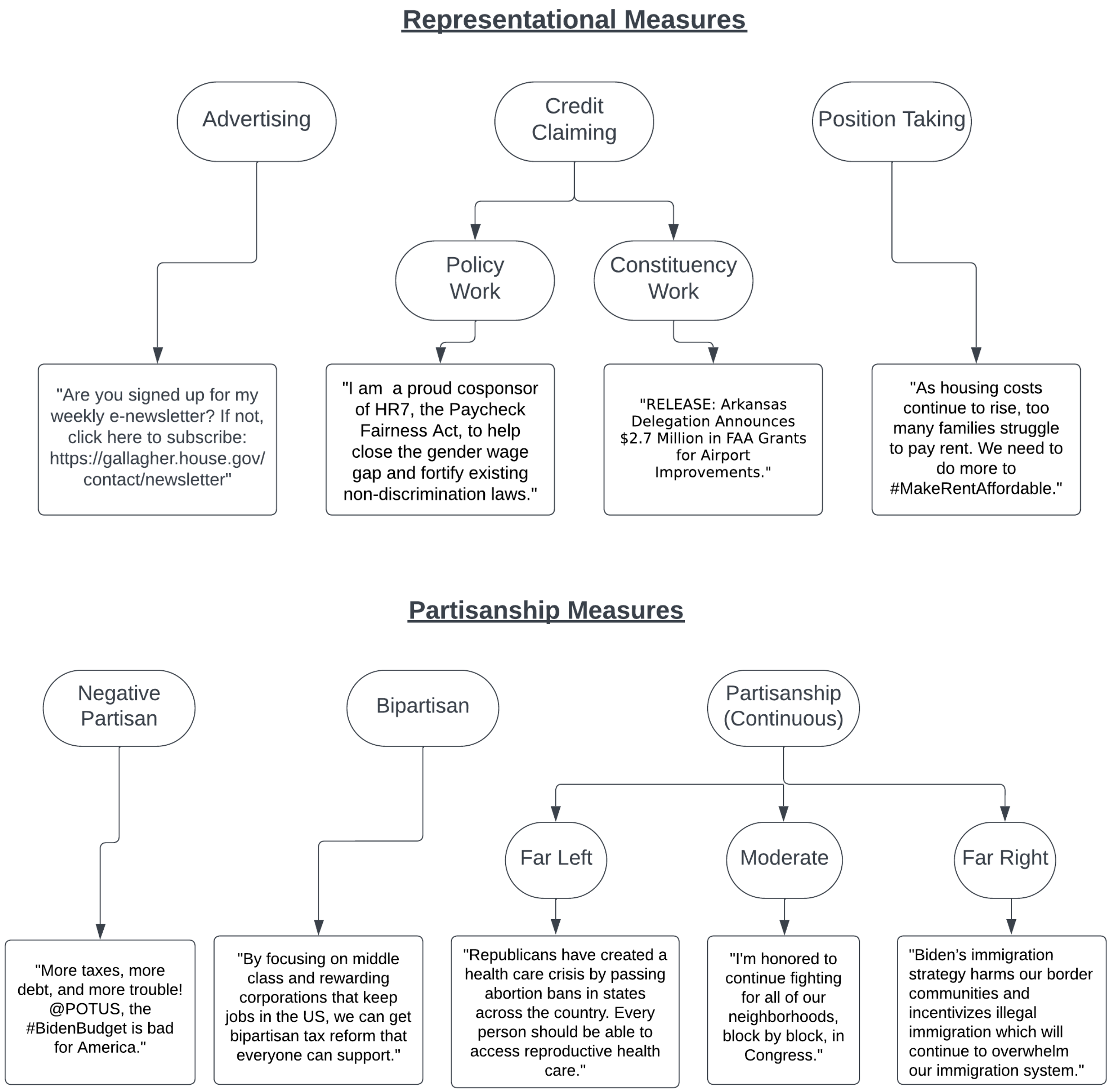
The partisanship categories mirror those studied by Russell (2018*b*); specifically, we identify both *Negative Partisanship* (an attack on the policies and politicians of the opposing party) and *Bipartisanship* (advocating the value of bipartisan collaboration) in messages.[3] In addition, we scale the *Partisan Orientation* of each message on a scale than ranges from -1 (most Democrat-leaning) to 0 (nonpartisan) to 1 (most Republican-leaning).

The categories are neither mutually exclusive nor collectively exhaustive. A single tweet could, for instance, advertise ("As the representative for TX-23, "…), position-take ("securing the border is one of my top priorities."), credit claim ("This is why I'm sponsoring legislation…"), and make a negative partisan attack ("The Biden border crisis must be stopped!"). It can also be none of the above, wishing (for example) followers a Merry Christmas or Happy Holidays.

In the following subsections, we describe our data collection, classification, and scaling methodology.

[3]Russell (2018*b*) also studies a third partisanship category, *Positive Partisanship*, messages that "signal favoritism or support for one's own party [or one's] party's candidates" (p. 703). We omit this category in our measurement for two reasons. First, the percent of messages that were positive partisan (as classified by our research assistants in the manually classified sample) was quite low, lower than other categories. Second, the accuracy of our supervised machine learning classifications was considerably lower for this category than all others, likely due to the small sample size.

FIGURE 1: Classification and Scaling Schemata With Example Text



Note: The figure displays the six separate classification categories and the continuous partisanship dimension our data contain. The top half of the figure displays the representation categories (Advertising, Credit Claiming for Policy Work, Credit Claiming for Constituency Work, and Position Taking), while the bottom half shows the partisanship categories (Negative Partisanship, Bipartisanship) and the continuous partisan dimension (Partisan Score). Example tweets classified into each category, as well as three tweets located at different points of the Partisan Score dimension, are shown to illustrate typical messages.

Data Collection

Our data come from two primary sources. For tweets and Facebook posts, data were downloaded from the platforms themselves (in the case of Facebook and Twitter/X). For newsletters, data come from the publicly available www.DCInbox.com repository of email newsletters collected and cleaned by Cormack (2017).[4] For newsletters, the data are available dating back to 2010; in the case of Twitter/X and Facebook, the data are available dating back to 2009. The dataset currently spans through 2022, although we aim to make periodic future updates of the dataset to broaden the timespan and enable study of contemporary congressional communication.

Table 1 displays the total number of tweets, Facebook posts, and email newsletters we possess, listed by biennial legislative session. As the table shows, online communication has increased considerable in volume. Comparing the 112th session of Congress (2011-2012), the first session for which we have complete data, to the 117th session of Congress (2021-2022), the number of tweets and Facebook posts shared by members of Congress each approximately tripled. The number of newsletters grew more modestly, increasing by approximately 35%. In total, the data consist of 7,827,972 unique communications from 1,025 US senators and representatives.

Classification Procedure

To classify messages into the six binary categories displayed in Figure 1, we used a combination of manual classification by trained research assistants combined with algorithmic, supervised machine machine learning. We began by classifying a stratified random sample of tweets posted by members of Congress across the time span, stratified to ensure an equal number of tweets for each chamber-year combination. 3,500 of these tweets were read separately by three members of the research team, who then made a binary decision for each category. In all categories the Krip-

[4]Our Twitter/X and Facebook data includes official, campaign, and personal account publicly associated with members of Congress.

TABLE 1: Online Communication by Members of Congress (2009 - 2022)

Medium	Session	Years	Percent Using	# (Median Member)	# (Total)
Tweets	111	2009-2010	–	–	71,155
	112	2011-2012	81.8	462.0	362,948
	113	2013-2014	89.4	826.5	604,771
	114	2015-2016	91.2	1065.0	713,981
	115	2017-2018	99.3	1306.5	975,185
	116	2019-2020	99.3	1741.0	1,266,550
	117	2021-2022	98.0	1683.0	1,139,215
Facebook Posts	111	2009-2010	–	–	51,023
	112	2011-2012	69.7	204.5	164,254
	113	2013-2014	81.0	276.0	204,511
	114	2015-2016	87.3	533.0	343,100
	115	2017-2018	91.0	747.0	474,591
	116	2019-2020	95.4	930.5	623,920
	117	2021-2022	97.1	1088.5	702,340
Newsletters	111	2009-2010	–	–	8,085
	112	2011-2012	89.0	27.0	21,711
	113	2013-2014	90.5	27.0	22,416
	114	2015-2016	92.6	30.0	23,962
	115	2017-2018	91.9	33.0	24,849
	116	2019-2020	92.4	43.0	30,558
	117	2021-2022	88.5	39.0	29,417

Note: The table displays the usage of tweets, Facebook posts, and email newsletters by members of Congress in our dataset. Percent Using and Number by Median Member are excluded for the 111th session, for which data spanning the full session do not exist.

pendorf's alpha was 0.90 or higher and the pairwise agreement rate was 0.98 or higher, indicating high levels of intercoder reliability. An additional 31,500 tweets were read and classified by a researcher.[5] Doing so resulted in a dataset of 35,000 manually classified tweets. After withholding 2,500 tweets for out-of-sample validation data, the remaining tweets were used as training data for a variety of supervised classification algorithms. Random forest models implemented using the `ranger` package in R produced the best balanced accuracy, the metric we used to select a classification algorithm.[6]

Out-of-sample classification performance metrics (accuracy, balanced accuracy, and F1 score) for each category of tweets are displayed in Table 2. The balanced accuracy for each category of tweets ranged from 0.76 to 0.89, values indicating satisfactory performance. Following the successful training of algorithms using the classified tweet data, our research team proceeded to classify an addition 2,500 sentence bigrams from a stratified random sample of Facebook posts and 2,500 sentence bigrams from a stratified random sample of email newsletters. The supervised classification algorithms trained from the tweet data were then applied to these unseen sentence bigrams to compare results. Classifier performance on these other communication media was lower than it was for the tweet data, but still within acceptable accuracy ranges, with balanced accuracy scores ranging from 0.64 to 0.83 depending on the category. For comparison's sake, the bottom of Table 2 displays the accuracy, balanced accuracy, and F1 score (as reported) for six recently published research articles classifying social media messages by members of Congress (Ballard et al. 2022, 2023; Yu, Wojcieszak, and Casas 2024), U.S. state legislators (Butler, Kousser, and Oklobdzija 2023; Payson et al. 2022), or both (Fowler et al. 2021).

[5]In addition to the tweets read by authors and research assistants, Annelise Russell contributed approximately 20,000 manually classified tweets from her research (Russell (2018*a*,*b*, 2021)).

[6]One feature of our classification procedure worth noting is that rather than assign a classification (e.g., advertising or not) based on a probability threshold of 0.50, as is typical, we instead chose a classification threshold for each category so that the number of expected false positives equaled the number of false negatives in the training data. Doing so ensures that, when the classification model is applied to the entire set of tweets or newsletter sentences for a given member, the false positives and false negatives cancel each other out, producing a close approximation to the true number of tweets or newsletter sentences in any given category. Results from the withheld out-of-sample validation data confirm that the number of false positives and false negatives closely offset for each category.

TABLE 2: Classification Accuracy Metrics, Our Supervised Models and Comparisons

Out-of-Sample Accuracy Metrics

Message Type	**Category**	**Accuracy**	**Balanced Accuracy**	**F1 Score**
Tweets	Advertising	0.83	0.80	0.72
	Credit Claiming (Constituency)	0.90	0.76	0.59
	Credit Claiming (Policy)	0.95	0.82	0.67
	Position Taking	0.78	0.77	0.82
	Bipartisanship	0.99	0.89	0.75
	Negative Partisanship	0.93	0.82	0.70
	Range:	0.78 - 0.99	0.76 - 0.89	0.59 - 0.82
Facebook Sentences	Advertising	0.86	0.76	0.62
	Credit Claiming (Constituency)	0.85	0.65	0.42
	Credit Claiming (Policy)	0.91	0.75	0.59
	Position Taking	0.78	0.80	0.79
	Bipartisanship	0.98	0.83	0.75
	Negative Partisanship	0.90	0.74	0.62
	Range:	0.78 - 0.98	0.65 - 0.83	0.42 - 0.79
Newsletter Sentences	Advertising	0.85	0.66	0.46
	Credit Claiming (Constituency)	0.78	0.69	0.51
	Credit Claiming (Policy)	0.86	0.79	0.66
	Position Taking	0.70	0.75	0.72
	Bipartisanship	0.96	0.75	0.63
	Negative Partisanship	0.88	0.64	0.43
	Range:	0.70 - 0.96	0.64 - 0.79	0.43 - 0.72

Comparisons From Other Published Work

Article		**Accuracy**	**Balanced Accuracy**	**F1 Score**
Fowler et. al. (2021)		0.80 - 0.99	0.50 - 0.95	–
Payson et. al. (2022)		0.55 - 0.59	–	0.35 - 0.92
Ballard et. al. (2022)		0.63 - 0.97	–	0.64 - 0.97
Ballard et. al. (2023)		–	–	0.75 - 0.94
Butler et. al. (2023)		0.20 - 0.99	–	–
Yu et. al. (2024)		0.66 - 0.74	0.67 - 0.85	0.50 - 0.77
	All:	0.20 - 0.99	0.50 - 0.95	0.35 - 0.97

Note: The top portion of the table displays the accuracy, balanced accuracy, and F1 score (out-of-sample) for each of the six representational categories for both the tweet and newsletter sentence data. The bottom portion of the table displays the equivalent metrics reported in recently published research articles using supervised classification techniques to classify social media messages by legislators, to give context for classifier performance.

As an additional validation for our classifications, in the Supplemental Materials we compare the communication styles members use to members' legislative styles, as introduced by Bernhard, Sewell, and Sulkin (2017) and discussed further in Bernhard and Sulkin (2018). These authors use a cluster analysis approach applied to behavioral data of Congressional actions (bill introductions and cosponsorships, party-line voting frequency, quantity of district offices and staff, etc.) to categorize members of the U.S. House into five distinct groupings: District Advocates, Policy Specialists, Party Builders, Party Soldiers, and Ambitious Entrepreneurs. While their data only extend until 2008, 1,079 members in our data served at least one session in the Bernhard and Sulkin data. For each of those members, we examine what percent of their tweets (Figure A.1) and Facebook posts (Figure A.2) fall into the different categories. As can be seen in the figures, there are clear differences in communication by members with different legislative styles. For example, District Advocates have high levels of credit claiming relative to other members, particularly credit claiming for constituency work. Similarly, Party Soldiers have the lowest levels of bipartisanship in their communications.

Scaling Procedure

To scale speech as more or less partisan, we adopt a similar methodological approach to Kaslovsky and Kistner (2024). We define speech as partisan on the basis of how strongly it identifies the party of the speaker. Extreme partisan speech is that used almost exclusively by members of one or the other party, while moderate speech is used by both. For instance, an individual who uses terms such as "border crisis" when discussing immigration is likely to be a Republican, while the utterance of "pathway to citizenship" means the speaker is likely to be a Democrat. Rhetoric is partisan if a speaker's language is dominated by terms used primarily by one party or the other.[7]

To capture this definition of partisanship, we apply a class affinity scaling model (Perry and Benoit 2017) to the words contained in the tweets, Facebook posts, and newsletters. While simi-

[7]Our approach can more precisely be described as measuring the *partisanship* of speech as opposed to *ideology*, given that partisan speech may encompass not just the discussion of policy issues, as in the examples above, but also non-policy topics, such as individual politicians (e.g., "crooked Hillary"). In practice, there is considerable overlap between the ideology and partisanship of speech.

lar in some respects to supervised text classification, this method is better described as a scaling procedure because it models speakers as having a continuous "affinity" towards classes (e.g., parties) rather than simply belonging to a binary class or not. In this model, affinity towards party (partisanship) is parameterized as $\pi_r \in [0,1]$, the probability that for any given token of speech W_i the underlying orientation of the speaker is $U_i = r$, or Republican. The probability that the speaker's underlying orientation is Democratic ($U_i = d$) for a given token of speech is thus $1-\pi_r$. The orientation of a speaker for each token $i = 1, \cdots, n$ determines the probability of a specific word w being used:

$$\Pr(W_i = w) = \pi_r \Pr(W_i = w | U_i = r) + (1-\pi_r)\Pr(W_i = w | U_i = d).$$

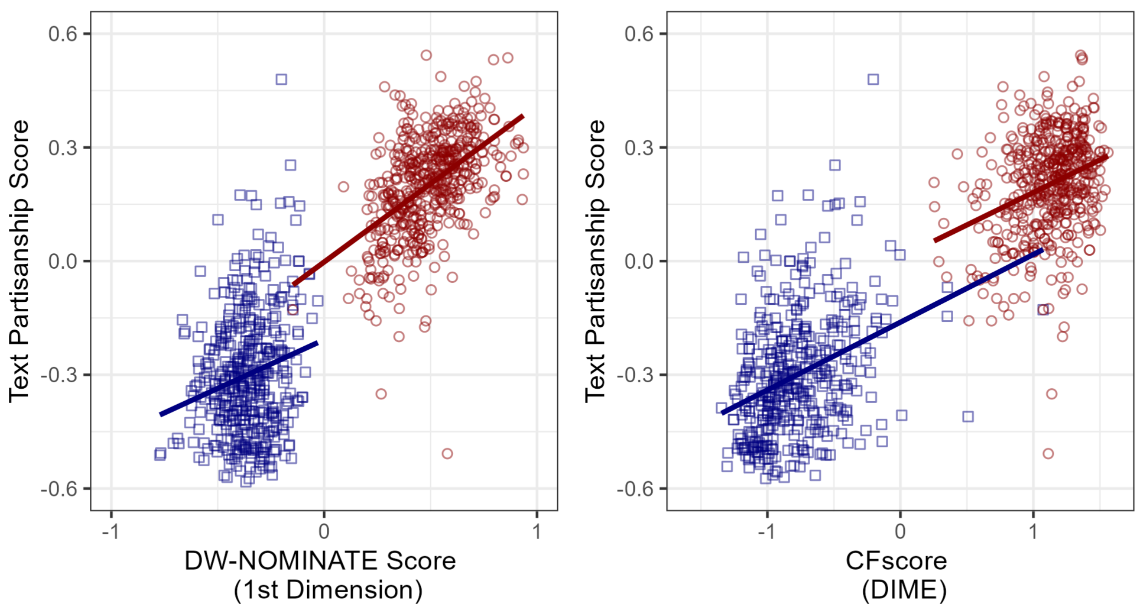
The partisanship for any given tweet, Facebook post, or newsletter is the expected proportion of time the underlying orientation is r versus d, which can be calculated as $\pi_r = \mathbb{E}\left\{\frac{1}{n}\sum_{i=1}^{n} U_i = r\right\}$. For interpretability sake, we rescale the resulting probability so it ranges from -1 (most Democrat-leaning) to 1 (most Republican-leaning), calculated as $2\pi_r - 1$. This rescaling we refer to as the Text Partisanship Score. This measure can be folded, i.e., $|2\pi_r - 1| \in [0,1]$, so that higher values indicate more extreme partisan rhetoric regardless of the speaker's party. This measure we refer to as the Text Partisan Extremity Score.

To validate this scaling, we aggregate to the member level by taking the average Text Partisanship Score across all texts (tweets, Facebook posts, and newsletters) in our dataset. These aggregated member-level Text Partisanship scores are then compared to two separate, commonly-used measures of Congressional ideology. Figure 2 compares a member's tweet or newsletter partisanship to the member's DW-NOMINATE score (Poole and Rosenthal 2000), which are estimated using roll call voting, and the member's campaign finance (CF) score (Bonica 2014), which are estimated using campaign contributions to the member.[8] While we view partisanship and ideology

[8]DW-NOMINATE score data is publicly available at www.voteview.com, while CFscores can be downloaded as www.data.stanford.edu/dime

as distinct conceptually, empirically the two are closely related. More ideologically extreme conservatives and liberals typically speak in more partisan ways, and vice-versa. DW-NOMINATE scores and CFscores thus each provide useful benchmarks for our text partisanship scores, representing two important domains (roll call voting and campaign finance) of American politics.

FIGURE 2: Comparing Text Partisanship Scores to Ideology Measures



Note: The figure displays the relationship between a member's average text partisanship score to the member's first dimension DW-NOMINATE score (on the left) or CFscore (on the right). Democrats are denoted with blue squares, Republicans with red circles. Within-party regression lines are displayed.

As Figure 2 shows, the average Text Partisanship Scores for members correlate with the member's ideology regardless of the ideology measure examined. This is true both in aggregate and within-party. The within-party correlation between text partisanship scores and DW-NOMINATE scores is 0.501 for Republicans, and 0.201 for Democrats. The within-party correlation between text partisanship scores and CF scores is 0.303 for Republicans, and 0.339 for Democrats.[9] These results indicate that the partisanship contained within the text of members'

[9]For comparison, the within-party correlation between DW-NOMINATE scores and CF scores is 0.577 for Republicans and 0.197 for Democrats. These within-party correlations are also similar to those of other ideology measures

tweets and newsletters is clearly related to both the way a member votes and whom a member raises money from, but distinct from each.

The Evolution of Online Congressional Communication

How has congressional rhetoric evolved in the age of social media? Our data, which span back to almost the beginning of widespread social media usage, are well equipped to answer this question.[10]

We first explore how *partisanship* in congressional rhetoric has evolved across time. Existing research has clearly demonstrated that polarization, measured via roll call voting patterns and in other ways, has been increasing in Congress during this time period.[11] Do we see an analagous increase in partisan rhetoric?

To evaluate this question, we plot the average Partisan Extremity Score by calendar day for all three communication media and each of the two major political parties across our entire time period. A smoothed GAM regression line is fit to each of the the time series, to flexibly capture changes across the period. The resulting plots are shown in Figure 3.

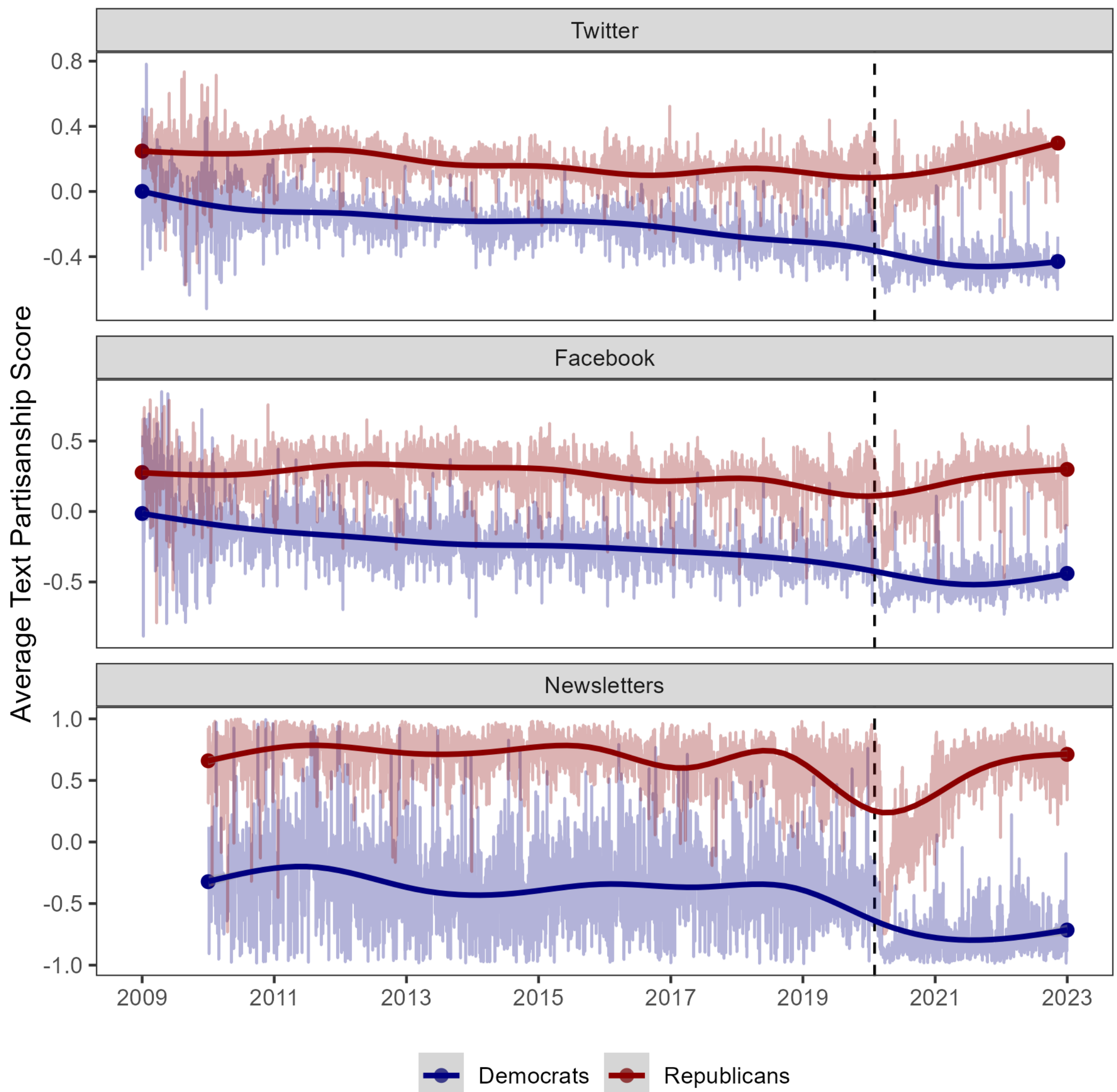
As can be seen in Figure 3, partisanship in Congressional rhetoric has grown steadily over this time period across all three forms of communication, but particularly on Facebook and Twitter. In 2009, the difference between the language used by Republicans and Democrats on social media was relatively small. The regression fit estimates that the average Text Partisanship Score of tweets (Facebook posts) by Democrats was approximately 0 (-0.01), compared to 0.25 (0.27) for Republicans, approximately a 12.5 percentage point gap in predictive difference. In contrast, by the end of 2022 the difference in the average tweet (Facebook post) Partisanship Score was

commonly used in political science research (Tausanovitch and Warshaw 2017). These within-party correlations are also similar to those obtained by Green et. al. (2024), who estimate the partisanship of newsletter and tweets and compare to DW-NOMINATE scores for House members during the 116th session of Congress.

[10]Both Facebook and Twitter first became available for public usage in 2006.

[11]For a summary of this research, see McCarty (2019).

FIGURE 3: Trends in Partisan Rhetoric (2009 - 2022)



Note: The figure displays the average Text Partisanship Score for tweets, Facebook posts, and newsletters each day from the beginning of 2009 to the end of 2022 (newsletter data begins in 2010). Trends shown separately for Democrats (blue) and Republicans (red). Dark lines indicate smoothed GAM regression lines of best fit. Dashed vertical line shows the beginning of the COVID-19 pandemic (February 2020).

0.73 (0.74), a 36.5 (37) percentage point gap. The change in partisanship in newsletters is more modest for each party, though again Democrats appear to be growing more partisan than Republicans.[12] In all cases the trend is gradual, with the sole exception of a Democratic shift towards the beginning of the COVID-19 pandemic.[13]

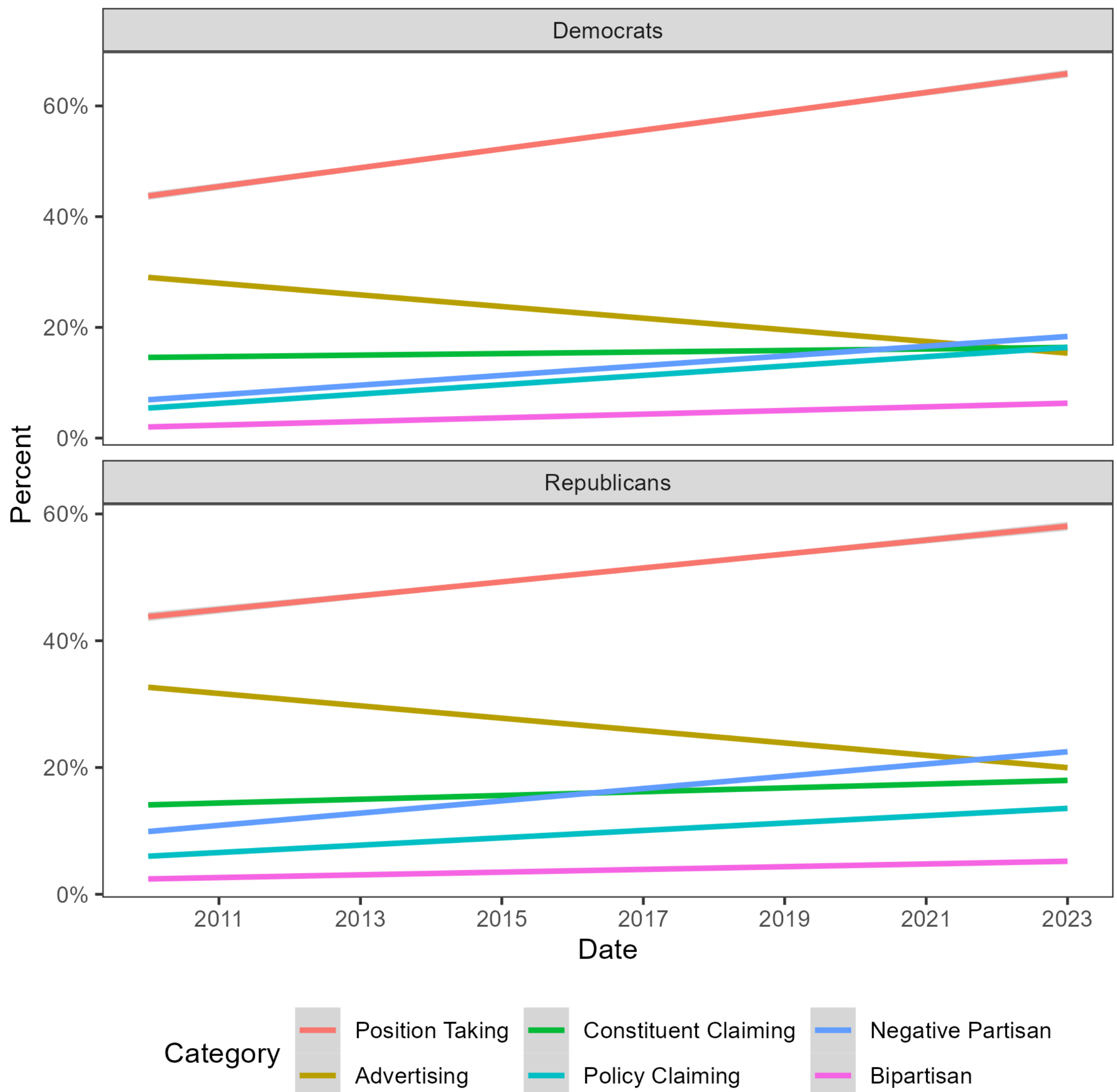
One noteworthy feature of this polarization in congressional rhetoric is that the growth in partisanship is driven almost entirely by Democrats. Across all three media the change in Text Partisanship Scores is at least 8 times as large for Democrats as it is for Republicans. From one perspective, this asymmetric polarization is surprising, given that (for a longer period of time than we have data here), roll call voting polarization in Congress appeared to be larger for Republicans than Democrats (McCarty 2019). On the other hand, the DW-NOMINATE scaling procedure has been criticized in recent years as failing to capture "ends-against-the-middle" voting dynamics that have become more common (Duck-Mayr and Montgomery 2023). Additionally, ideal point scaling of state legislators shows Democrats moving farther to the left than Republicans have moved towards the right during the time period studied here, supporting the idea that the 2010s was a decade of increasing liberalism among Democratic office-holders (Shor and McCarty 2022).

In addition to studying changes in the average partisanship of rhetoric by members of Congress, we can also evaluate change in the purpose of communications, decomposed into the six categories described above. Figure 4 shows how the frequency of these communication types has evolved over time, displayed as simple linear trends aggregated across tweets, Facebook posts, and newsletters, for ease of visualization. As can be seen in the Figure, the two largest changes

[12]While the change in partisan divergence is more pronounced on social media, both the starting and ending magnitude of the difference between Democrats and Republicans is larger for newsletters. This is partially an artifact of the longer document lengths for newsletters, which make predicting partisanship an easier task than in shorter tweets or Facebook posts. When the unit of analysis is changed to sentence bigrams from newsletters instead (a length of test approximately equal to the typical tweet or Facebook post), there is less partisan difference in newsletters.

[13]During this period of time members of both parties devoted a considerable portion of their communication to discussing the threat of the pandemic. After a few months this changed, so that only Democrats discussed the pandemic in these terms. The scaling model associates this language with Democrats, which makes Republicans look more moderate for a brief period.

FIGURE 4: Trends in Communication Purpose (2010 - 2022)



Note: The figure displays linear trends in the average percent of congressional communication (aggregating tweets, Facebook posts, and newsletters) classified into each of the six classification categories for both of the two major parties between 2010 and 2022.

are an increase in Position Taking and Negative Partisanship over the thirteen year time period. For Democrats, Position Taking is observed in approximately two-thirds (66.6%) of communications by the end of 2022, compared to 46% of communications at the beginning of 2010. For Republicans, Position Taking grows from approximately 47% of communications to 60%, a smaller but still considerable change. Negative Partisanship over doubles for Democrats, growing from 9% to 19%, while for Republicans, Negative Partisan messages grow from making up 14% of all messages to 25%. Most other communication categories grow as well during this time period, albeit more modestly. The sole exception is advertising, which becomes less common.

To summarize, the partisanship scalings and message classifications both tell a consistent message. In the years since social media has emerged and become ubiquitous both among the public as well as elected officeholders, online communication has become more partisan and more negative in tone. Attributing causality to these trends is beyond the scope of this paper, though the data we introduce may help in this task. Despite this, in the following section we explore one potential mechanism that may be contributing to these dynamics, a mechanism we term the social media feedback mirage.

The Social Media Feedback Mirage

One advantage of our new dataset is that we can analyze the relationship between rhetorical content – the partisanship and purpose, as measured via scaling and classification – and public response at the level of an individual message. Fortunately, social media data is well-equipped for such an analysis, as data on posts and tweets include metrics measuring the amount of positive engagement each message receives, in the form of likes, shares, retweets, etc.

We first use our data to compare the amount of positive engagement each tweet receives depending on the content of the tweet.[14] To accomplish this, we estimate a series of OLS regression models where the unit of observation is an individual tweet. For each tweet, we include six binary variables for whether the tweet is classified into each of our categories, as well as the continu-

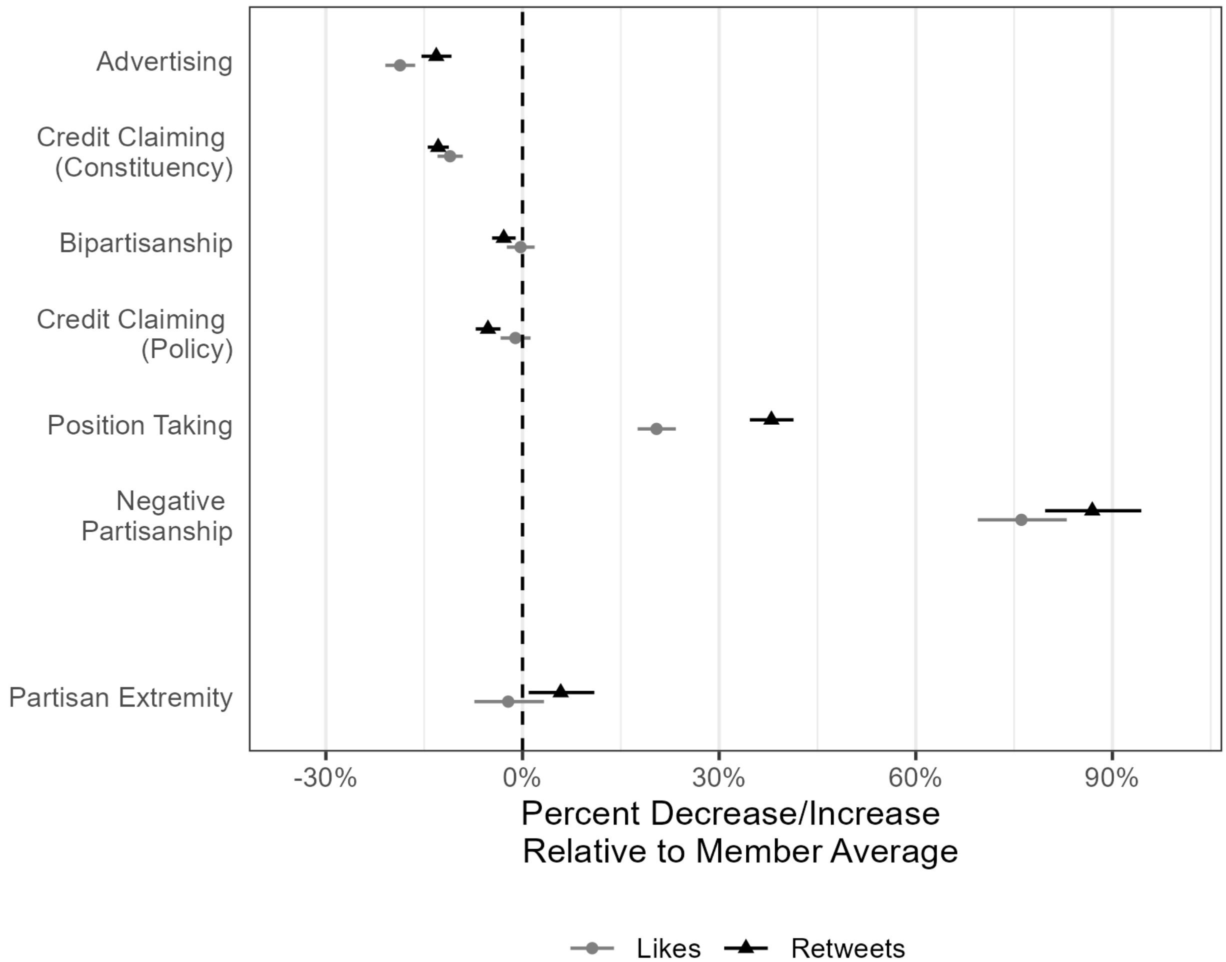
[14] We have yet to analyze the relationship between positive engagement and message content on Facebook, although this is a next step for the project.

ous (0 to 1) Tweet Partisan Extremity Score. The dependent variable is the number of likes or retweets (logged to address right-skew). Because we have many observations per member, here we include member fixed effects rather than including control variables. As a consequence, coefficients can be interpreted as the difference in expected likes or retweets relative to the average tweet by a member that is not extreme and does not credit claim, advertise, position-take, etc. We also include legislative session fixed effects, to account for changes in engagement and messaging across time.

The full set of results are displayed in tabular form in Table B.1 in the Supplemental Materials, but here we present the results graphically. As can be seen in Figure 5, there are clear differences in positive engagement across message types. The most striking pattern is the high levels of engagement negative partisanship receive. Negative partisan attacks on social media are associated with a 76% increase in likes and an 87% increase in retweets, almost doubling the positive engagement a typical tweet by a member of Congress usually merits. Position Taking tweets also receive considerably more retweets (38%) and likes (20%) than the typical tweet. Finally, more extreme partisan tweets receive significantly more retweets, but not likes. On the other hand, Advertising tweets receive significantly fewer likes (-19%) and retweets (-13%) than the member's average. Credit Claiming for Constituent Work also results in significantly less positive engagement.

Does this difference in message reception by social media users matter? On the one hand, reelection-focused members should care most about how communication styles shape the views of voters in their districts and states. On the other hand, social media sites like Twitter provide instantaneous feedback on message reception to legislators and their staffs in a way that they do not receive from other forms of communication or other audiences. There exists potential for legislators to mistake approval on social media with broader approval, which may lead legislators to engage in more such rhetoric. While the evidence at this point is only suggestive, it is noteworthy that the messaging types that have increased in frequency the most during the era of growing social media usage – position taking, negative partisanship, and extreme partisan

FIGURE 5: MESSAGE CONTENT AND TWITTER ENGAGEMENT



Note: The figure displays OLS coefficient estimates and 95% confidence intervals from the full model results shown in Table B.1. Coefficient estimates are transformed ($\exp(\hat{\beta}) - 1$) to percent differences for interpretability. Independent variables, shown on the y-axis, include tweet style and partisanship. All models include member fixed effects, meaning the coefficient represents the number of likes or retweets relative to a member's average. Standard errors are clustered by member.

rhetoric, as shown in Figures 3 and 4 – are the exact types of messages that receive the most positive engagement on social media.

If social media users approve of partisan, negative, and position-taking messages, do voters? Two forms of evidence suggest the answer is no. First, experimental studies (Costa 2021; Simas et al. 2025) conducted using nationally representative samples of Americans have compared how citizens react to negative partisan attacks relative to other types of messaging. These studies show that survey respondents report lower satisfaction with and intention to vote for legislators who use negative partisanship in their messaging. Simas et. al. also examine how position-taking messages compare to advertising and credit claiming messages. Unlike what we observe in the social media engagement metrics, they do not find significant differences between responses to credit claiming and position-taking messages (although both types of messaging are preferred on average to advertising messages).

One potential critique of this work is that it does not take into account the preferences of members' constituents. Even if national voters do not approve of partisan rhetoric, perhaps residents living in a member's district or state do. To evaluate this possibility, we take advantage of constituency approval ratings contained in the Cooperative Election Study (CES) surveys.[15] The CES samples respondents from across the United States but identifies each respondent's Congressional district. The surveys ask each respondent how much they approve of their representative and two senators on a four-point scale ranging from Strongly Approve to Strongly Disapprove.

For each member in each legislative session between the from the 113th session of Congress onwards, we evaluate whether differences in communication style are associated with higher or lower approval rating. Specifically, we use a series of multivariate OLS regressions to examine whether the number of tweets or Facebook posts (logged to address right-skew), the average Text Partisan Extremity Score, or the percent of messages in each of the six categories for each of the two communication forms predict how approving constituents are of their representatives. A variety of control variables and fixed effects are included to account for other factors that may affect both approval rating and member communication.[16] We control for the partisanship of a member's district or state (measured using presidential vote share), the member's seniority within

[15]Date are publicly available at www.cces.gov.harvard.edu/

[16]All control variables come from updates to Volden and Wiseman (2014; 2018), and can be downloaded at https://thelawmakers.org/data-download.

the chamber, whether the member is a party leader, whether they are a committee chair, whether the member is a woman, whether the member is black, and whether the member is Hispanic. We include party-session fixed effects, which address any across-time fluctuations in approval for Democrats and Republicans, and also account for differences in approval between members in the majority versus the minority. Finally, we include state fixed effects, to account for differences in average approval rating by state.[17] Standard errors are clustered by individual members, to account for non-independence of errors when the same members is in the dataset for multiple sessions.

A table with the full set of results for these regression models can be found in Table B.2 in the Supplemental Materials. The results of interest are displayed in Figure 6. Separate models are estimated using a member's average approval rating among all respondents (mean = 2.9, SD = 0.3), independents (mean = 2.7, SD = 0.4) and same party respondents (mean = 3.3, SD = 0.2), as members may in particular care about the opinions of these latter two groups, given their importance in the general election and primary election respectively.

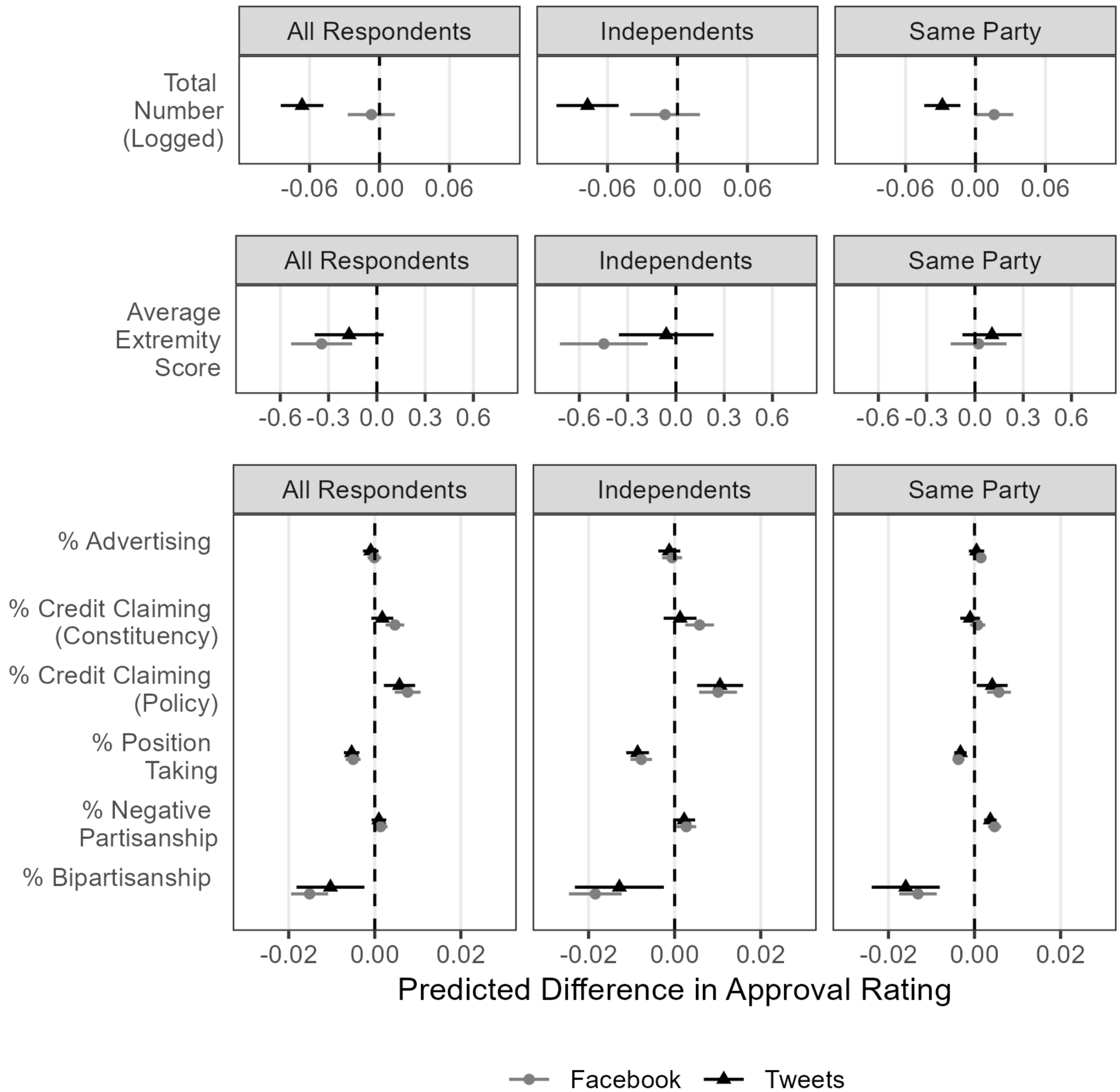
Figure 6 reveals several key points. First, members who tweet more have lower approval ratings among their constituents, on average, a finding that is consistent regardless of whether one considers all constituents, just independents, or just same-party constituents. In contrast, there is no significant relationship between posting on Facebook and approval ratings.

Second, members who use more extreme rhetoric on Facebook receive lower approval ratings from constituents writ large and independents in particular. The coefficient on extreme rhetoric in tweets is also negative, though not statistically significant. Even among same-party constituents, there is no significant increase in approval ratings associated with more extreme rhetoric.

Finally, if we consider how often members send messages of the various representational and partisanship categories we measure, the strongest (positive) relationship we observe is that

[17] We do not include member fixed effects. While including these would strengthen our ability to draw causal inferences, because of the small number of sessions per member, these estimates would be very imprecise, potentially producing misleading results.

FIGURE 6: Communication Style and Constituent Approval



Note: The figure displays OLS coefficient estimates and 95% confidence intervals from the full model results shown in Table B.2. The dependent variable is the average CES approval rating (for all respondents, independent respondents, and respondents of the same party as the member, respectively). All models include control variables and fixed effects, with standard errors clustered by member.

members who claim credit for policy work have the highest constituent approval, among all three types of constituents. In contrast position taking and bipartisanship have negative associations with approval ratings. Members who use negative partisanship do not have higher approval ratings among constituents writ large, although there is a small positive relationship with approval ratings among same party members.

This evidence, combined with the experimental work cited above, makes clear that there are meaningful differences between what types of messaging social media users value versus what types of messaging voters value. Posts on social media that feature negative partisanship, position-taking, and extreme rhetoric receive high levels of positive engagement from users on the side, feedback that legislators and staff receive near instantaneously. In contrast, the typical citizen and the typical constituent respond most positively to other types of messaging, such as credit claiming. While ultimately re-election motivated legislators may care most about how the median voter responds to messaging, they receive signals of this sort far less frequently and directly than the signals they receive on social media.

This potentially misleading discrepancy we identify here we term the *social media feedback mirage*. If legislators and their staff respond to the feedback they receive to messaging on social media, social media has the potential to amplify content that ultimately alienates broader voters.

Conclusion

In this paper, we introduce a new dataset of online congressional communication: the Scaled and Classified Congressional Communication (SCCC) dataset. Our dataset has three features that allow it to answer more questions than ever before. First, the data span 14 years, nearly the entire era of social media usage by political elites. Second, the data are multi-modal, including two of the largest social media sites and email newsletters. Third, we have measures of both representation and partisanship, enabling researchers to consider how both important characteristics of political communication affect key political outcomes, such as how voters view members of Congress.

The analyses in this paper, while only an initial demonstration of the possibilities our data unlock, produce important findings. Two in particular stand out. First, there is a clear difference in the rhetoric constituents approve of versus the rhetoric social media users reward. While constituents report higher approval of members who talk more about their accomplishments in office and lower approval for members who use partisan rhetoric, on Twitter/X this pattern is reversed. More partisan rhetoric, and in particular negative partisan rhetoric, receives the most likes and retweets. Second, and potentially related to the first finding, over time members have been using more partisan and more negative rhetoric, in newsletters but especially on Twitter/X. These findings warrant more research, particularly to determine if partisan and negative rhetoric by politicians on social media leads to more of the same by the mass public.

Several other possible research avenues using our data stand out as particularly promising. This includes a more detailed examination of how Congressional communication changes over the election cycle (e.g., how do members communicate before and after primary elections?), or how the messaging a member sends evolves over the course of their career (e.g. do styles change as members advance within the party?). Our hope is that this data can be a boon to researchers in the field working on topics of political communication, congressional representation, and rhetoric more broadly.

And while we highlight the fact that we offer data on both style and partisanship, the partisanship ratings alone can provide yet another tool for those researching such topics as polarization, candidate positioning, and the congruence between members of Congress and those they represent. The two widely-used measures of legislative positioning we draw on above are derived from legislative voting and fundraising. Though the public has access to records of both, the majority of individuals lack knowledge about their representatives' activities in these areas. Our ratings, in contrast, are derived from highly visible and easily accessible communications that are crafted to portray a legislator as they want to be seen. So when used in combination with these other types of measures, our partisan scaling has the potential to offer a more complete picture of a legislators' preferences and speak to questions of whether those preferences appear relatively consistent when approximated from these different sources. Because while the nature of politics and political communication has changed drastically in the past half century, the fact remains that "if there is to be congruence between the policy preferences of the represented and the policy decisions of the representatives, however, two-way communication between them is a prerequisite" (Fenno 1978, p. 241). Thus, we are offering one more resource for the continuing and evolving study of representation in the U.S.

References

Ballard, Andrew O., Ryan DeTamble, Spencer Dorsey, Michael Heseltine, and Marcus Johnson. 2023. "Dynamics of Polarizing Rhetoric in Congressional Tweets." *Legislative Studies Quarterly* 48 (1): 105–144.

Ballard, Andrew, Ryan DeTamble, Spencer Dorsey, Michael Heseltine, and Marcus Johnson. 2022. "Incivility in Congressional Tweets." *American Politics Research* 50 (6): 769–780.

Bernhard, William. 2018. *Legislative Style.* Chicago studies in American politics. The University of Chicago Press.

Bernhard, William, Daniel Sewell, and Tracy Sulkin. 2017. "A Clustering Approach to Legislative Styles." *Legislative Studies Quarterly* 42 (3): 477–506.

Blum, Rachel, Lindsey Cormack, and Kelsey Shoub. 2023. "Conditional Congressional Communication: How Elite Speech Varies Across Medium." *Political Science Research and Methods* 11 (2): 394–401.

Bonica, Adam. 2014. "Mapping the Ideological Marketplace." *American Journal of Political Science* 58 (2): 367–386.

Burke, Edmund. 1774. "Speech to the Electors of Bristol." In *The Works of the Right Honourable Edmund Burke.* Vol. 1 London: Henry G. Bohn pp. 446–448. Published 1854–56.

Butler, Daniel M., Thad Kousser, and Stan Oklobdzija. 2023. "Do Male and Female Legislators Have Different Twitter Communication Styles?" 23 (2): 117–139.

Cormack, Lindsey. 2016. "Extremity in Congress: Communications versus Votes." *Legislative Studies Quarterly* 41 (3): 575–603.

Cormack, Lindsey. 2017. "DCinbox - Capturing Every Congressional Constituent E-newsletter from 2009 Onwards." *The Legislative Scholar* 2 (1): 27–36.

Costa, Mia. 2021. "Ideology, Not Affect: What Americans Want from Political Representation." *American Journal of Political Science* 65 (2): 342–358.

Cowburn, Mike, and Marius Sältzer. 2024. "Partisan Communication in Two-Stage Elections: The Effect of Primaries on Intra-Campaign Positional Shifts in Congressional Elections." *Political Science Research and Methods* pp. 1–20.

Duck-Mayr, JBrandon, and Jacob Montgomery. 2023. "Ends Against the Middle: Measuring Latent Traits when Opposites Respond the Same Way for Antithetical Reasons." *Political Analysis* 31 (4): 606–625.
URL: *https://www.cambridge.org/core/journals/political-analysis/article/abs/ends-against-the-middle-measuring-latent-traits-when-opposites-respond-the-same-way-for-antithetical-reasons/0D5C5678D2DA99CB96A37AD46CD8A6EE*

Evans, Heather K., and Jennifer Hayes Clark. 2016. ""You Tweet Like a Girl!": How Female Candidates Campaign on Twitter." *American Politics Research* 44 (2): 326–352.

Evans, Heather K., Victoria Cordova, and Savannah Sipole. 2014. "Twitter Style: An Analysis of How House Candidates Used Twitter in Their 2012 Campaigns." *PS: Political Science & Politics* 47 (2): 454–462.

Fenno, Richard F. 1978. *Home Style: House Members in Their Districts.* Scott, Foresman.

Fowler, Erika Franklin, Michael M. Franz, Gregory J. Martin, Zachary Peskowitz, and Travis N. Ridout. 2021. "Political Advertising Online and Offline." 115 (1): 130–149.

Frankel, Laura Lazarus, and D. Sunshine Hillygus. 2017. "Niche Communications in Political

Campaigns." In *The Oxford Handbook of Political Communication*, ed. Kate Kenski, and Kathleen Hall Jamieson. Oxford University Press.

Gainous, Jason, and Kevin M. Wagner. 2013. *Tweeting to Power: The Social Media Revolution in American Politics.* Oxford University Press.

Green, Jon, Kelsey Shoub, Rachel Blum, and Lindsey Cormack. 2024. "Cross-Platform Partisan Positioning in Congressional Speech." *Political Research Quarterly* p. 10659129241236685.

Grimmer, Justin. 2013. *Representational Style in Congress: What Legislators Say and Why It Matters.* Cambridge University Press.

Grossmann, Matt, and David A. Hopkins. 2016. *Asymmetric Politics: Ideological Republicans and Group Interest Democrats.* Oxford University Press.

Hemphill, Libby, Annelise Russell, and Angela M. Schöpke-Gonzalez. 2021. "What Drives U.S. Congressional Members' Policy Attention on Twitter?" *Policy & Internet* 13 (2): 233–256.

Jungherr, Andreas. 2014. "The Logic of Political Coverage on Twitter: Temporal Dynamics and Content." *Journal of Communication* 64 (2): 239–259.

Kaslovsky, Jaclyn, and Michael R. Kistner. 2024. "Responsive Rhetoric: Evidence from Congressional Redistricting." *Legislative Studies Quarterly* 49 (4).

Mansbridge, Jane. 2003. "Rethinking Representation." *The American Political Science Review* 97 (4): 515–528.

Mayhew, David R. 1974. *Congress: The Electoral Connection.* Yale University Press.

McCarty, Nolan. 2019. *Polarization: What Everyone Needs to Know.* Oxford‘: Oxford University Press.

McKee, Seth C., Heather K. Evans, and Jennifer Hayes Clark. 2022. "The "PERFECT" Call: Congressional Representation by Tweet in the Midst of the Ukraine Whistleblower Scandal." *American Politics Research* 50 (1): 30–44.

Munger, Kevin. 2023. "Temporal Validity as Meta-Science." *Research & Politics* 10 (3): 1–10.

Payson, Julia, Andreu Casas, Jonathan Nagler, Richard Bonneau, and Joshua A. Tucker. 2022. "Using Social Media Data to Reveal Patterns of Policy Engagement in State Legislatures." 22 (4): 371–395.

Perry, Patrick O., and Kenneth Benoit. 2017. "Scaling Text with the Class Affinity Model." *arXiv* .
URL: *https://arxiv.org/abs/1710.08963*

Pitkin, Hanna F. 1967. *The Concept of Representation.* University of California Press.

Poole, Keith T., and Howard Rosenthal. 2000. *Congress: a Political-Economic History of Roll Call Voting.* Oxford University Press.

Russell, Annelise. 2018*a*. "The Politics of Prioritization: Senators' Attention in 140 Characters." *The Forum* 16 (2): 331–356.

Russell, Annelise. 2018*b*. "U.S. Senators on Twitter: Asymmetric Party Rhetoric in 140 Characters." *American Politics Research* 46 (4): 695–723.

Russell, Annelise. 2021. *Tweeting is Leading: How Senators Communicate and Represent in the Age of Twitter.* Oxford University Press.

Scherpereel, John A., Jerry Wohlgemuth, and Audrey Lievens. 2018. "Does Institutional Setting Affect Legislators' Use of Twitter?" *Policy & Internet* 10 (1): 43–60.

Shor, Boris, and Nolan McCarty. 2022. "Two Decades of Polarization in American State Legislatures." *Journal of Political Institutions and Political Economy* 3 (3–4): 343–370.
URL: *https://www.nowpublishers.com/article/Details/PIP-0063*

Simas, Elizabeth N., David Hilden, Michael R. Kistner, and Jamie Wright. 2025. "Credit Claiming and Accountability for Legislative Effectiveness." *Center for Effective Lawmaking Working Paper Series* .

URL: *https://thelawmakers.org/wp-content/uploads/2025/01/Credit$_C$laiming.pdf*

Smith, Sarah A., and Annelise Russell. 2022. "Different Chambers, Divergent Rhetoric: Institutional Differences and Policy Representation on Social Media." *American Politics Research* 50 (6): 792–797.

Straus, Jacob R., Raymond T. Williams, Colleen Shogan, and Matthew Glassman. 2016. "Congressional Social Media Communications: Evaluating Senate Twitter Usage." *Online Information Review* 40 (5): 643–659.

Tausanovitch, Chris, and Christopher Warshaw. 2017. "Estimating Candidates' Political Orientation in a Polarized Congress." *Political Analysis* 25 (2): 167–187.

Tillery, Alvin B. 2021. "Tweeting Racial Representation: How the Congressional Black Caucus Used Twitter in the 113th Congress." *Politics, Groups, and Identities* 9 (2): 219–238.

Tucker, Joshua, Andrew Guess, Pablo Barbera, Cristian Vaccari, Alexandra Siegel, Sergey Sanovich, Denis Stukal, and Brendan Nyhan. 2018. "Social Media, Political Polarization, and Political Disinformation: A Review of the Scientific Literature." *SSRN Electronic Journal* .

URL: *https://www.ssrn.com/abstract=3144139*

Volden, Craig, and Alan E. Wiseman. 2014. *Legislative Effectiveness in the United States Congress: the Lawmakers.* New York: Cambridge University Press.

Volden, Craig, and Alan E. Wiseman. 2018. "Legislative Effectiveness in the United States Senate." *The Journal of Politics* 80 (2): 731–735.

Yiannakis, Diana Evans. 1982. "House Members' Communication Styles: Newsletters and Press Releases." *The Journal of Politics* 44 (4): 1049–1071.

Yu, Xudong, Magdalena Wojcieszak, and Andreu Casas. 2024. "Partisanship on Social Media: In-Party Love Among American Politicians, Greater Engagement with Out-Party Hate Among Ordinary Users." *Political Behavior* 46 (2): 799–824.

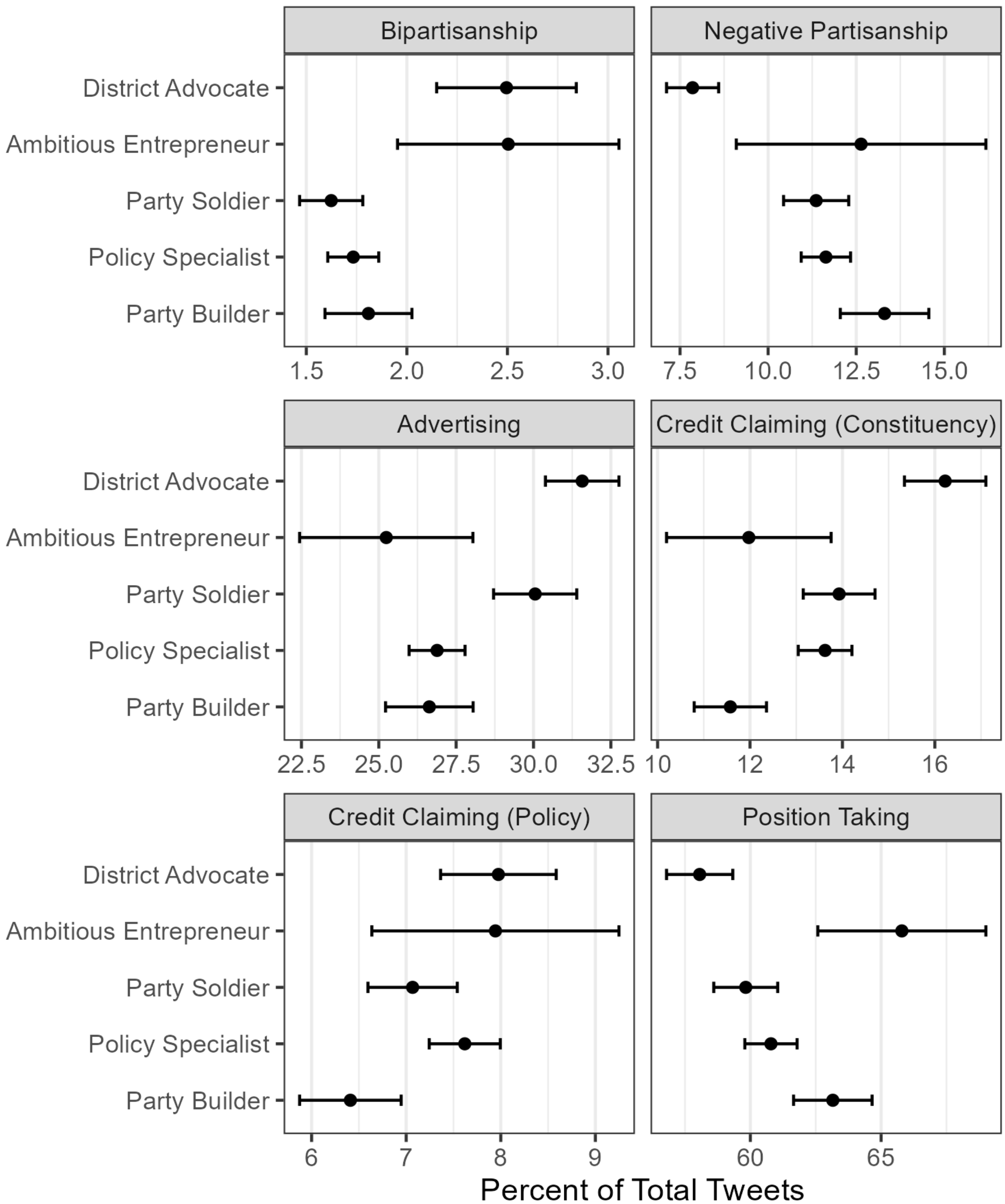
Supplementary Materials

Measuring Partisanship and Representation in Online Congressional Communication

Contents

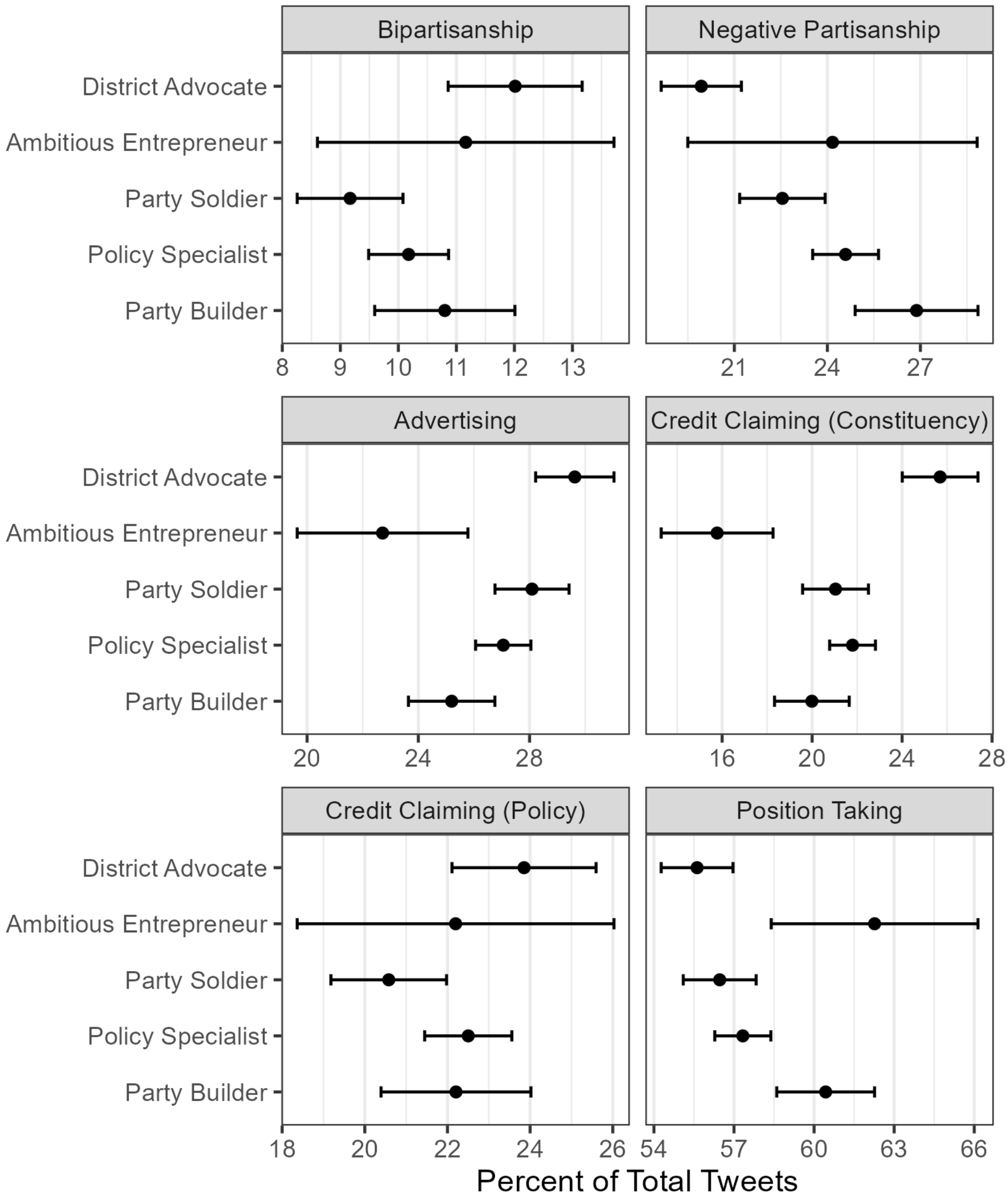
A Comparing Communication Styles to Legislative Styles

FIGURE A.1: DIFFERENCES IN TWITTER RHETORIC BY LEGISLATIVE STYLE



Note: The figure displays the average percent of a member's tweets classified as each of the six categories for the five legislative styles as measured by Bernhard and Sulkin (2018). Error bars display the 95% confidence interval for each point estimate.

FIGURE A.2: DIFFERENCES IN FACEBOOK RHETORIC BY LEGISLATIVE STYLE



Note: The figure displays the average percent of a member's Facebook posts classified as each of the six categories for the five legislative styles as measured by Bernhard and Sulkin (2018). Error bars display the 95% confidence interval for each point estimate.

B Full Tables of OLS Regression Results

TABLE B.1: Full Table of Estimates for Figure 5

	Dependent Variable	
	# Likes	# Retweets
Advertising Tweet	-0.207**	-0.141**
	(0.009)	(0.008)
Credit Claiming (Constituency) Tweet	-0.117	-0.138**
	(0.040)	(0.013)
Policy Claiming (Constituency) Tweet	-0.011	-0.054**
	(0.012)	(0.007)
Position Taking Tweet	0.186**	0.322**
	(0.005)	(0.009)
Negative Partisanship Tweet	0.566**	0.626**
	(0.045)	(0.042)
Bipartisanship Tweet	-0.003	-0.029
	(0.024)	(0.016)
Tweet Extremity Score	-0.022	0.057*
	(0.016)	(0.017)
Member FEs	Y	Y
Session FEs	Y	Y
Num.Obs.	3,292,184	3,292,184
R2 Adj.	0.475	0.473

Table displays coefficient from OLS models.

Standard errors clustered by member shown in parentheses. *$p<0.05$; **$p<0.01$

TABLE B.2: Full Table of Estimates for Figure 6

	DV: Average Approval Rating					
	All Respondents		Independents		Same Party	
	(1)	(2)	(3)	(4)	(5)	(6)
Total Number	-0.066**	-0.007	-0.077**	-0.011	-0.028**	0.016
	(0.009)	(0.010)	(0.014)	(0.015)	(0.008)	(0.008)
Average Extremity Score	-0.172	-0.343**	-0.060	-0.448**	0.106	0.023
	(0.109)	(0.097)	(0.150)	(0.139)	(0.094)	(0.089)
Pct. Advertising	-0.001	0.000	-0.001	-0.001	0.000	0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Pct. Credit Claiming (Constituency)	0.002	0.005**	0.001	0.006**	-0.001	0.001
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Pct. Credit Claiming (Policy)	0.006**	0.008**	0.011**	0.010**	0.004*	0.006**
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.001)
Pct. Position Taking	-0.005**	-0.005**	-0.009**	-0.008**	-0.003**	-0.004**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Pct. Negative Partisanship	0.001	0.001	0.002	0.003*	0.004**	0.005**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Pct. Bipartisanship	-0.010*	-0.015**	-0.013*	-0.018**	-0.016**	-0.013**
	(0.004)	(0.002)	(0.005)	(0.003)	(0.004)	(0.002)
District Dem. Pres. Voteshare	0.100	0.019	0.219	0.107	-0.163*	-0.156*
	(0.093)	(0.090)	(0.132)	(0.131)	(0.075)	(0.077)
District Partisan Favorability	0.991**	1.035**	0.580**	0.665**	0.204**	0.170*
	(0.088)	(0.086)	(0.126)	(0.127)	(0.071)	(0.076)
Woman	-0.012	-0.022	-0.043	-0.043	0.029*	0.022
	(0.017)	(0.017)	(0.025)	(0.026)	(0.014)	(0.014)
AfricanAmerican	-0.023	-0.026	0.007	0.002	-0.003	0.006
	(0.027)	(0.025)	(0.042)	(0.041)	(0.021)	(0.021)
Hispanic	-0.039	-0.063*	-0.052	-0.089*	-0.076**	-0.078**
	(0.032)	(0.032)	(0.043)	(0.044)	(0.026)	(0.026)
Party Leader	-0.048	-0.077*	-0.097*	-0.123**	0.002	-0.023
	(0.031)	(0.033)	(0.043)	(0.046)	(0.026)	(0.028)
Committee Chair	-0.113**	-0.134**	-0.155**	-0.174**	-0.060*	-0.073**
	(0.024)	(0.025)	(0.034)	(0.037)	(0.023)	(0.025)
Data	Twitter	Facebook	Twitter	Facebook	Twitter	Facebook
Party-Session FEs	Y	Y	Y	Y	Y	Y
State FEs	Y	Y	Y	Y	Y	Y
Seniority FEs	Y	Y	Y	Y	Y	Y
Num.Obs.	2432	2245	2431	2245	2432	2245
R2 Adj.	0.477	0.490	0.305	0.306	0.253	0.267

Table displays coefficient from OLS models. Standard errors clustered by member shown in parentheses. *p<0.05; **p<0.01