Power and the Tweet:

How Viral Messaging Conveys Political Advantage

Abstract

Researchers are increasingly confronting the need to examine the impacts of social media on democratic discourse. Analyzing 55,560 tweets from the official Twitter accounts of the Democratic and Republican parties in the United States, we examine approaches used by political parties to encourage sharing of their content within the contemporary political divide. We show that tweets sent by the Republican Party are more likely to be predominant in the language of assessment and that tweets predominant in the language of assessment lead to more retweets. Further, this effect is reduced as political parties gain control of successive branches of government. This is because successive increases in political power create fewer impediments to the implementation of a party's political agenda. As impediments to action are reduced, so is regulatory fit for assessment-oriented language. Goal pursuit language shared on Twitter therefore reveals distinct approaches to obtaining and dealing with power across the U.S. political system, and constitutes an important tool for public policy makers to use in successfully conducting policy debates.

Political parties and their candidates need their content to be shared during campaigns and while in government. This is not only because a party's campaign will influence whether they are likely to win an election (Farrell and Schmitt-Beck 2002; Holbrook 1996), but also because their electoral positioning and policy framing will determine the mandate on which they have to govern when in power (Shamir, Shamir, and Sheafer 2008). Moreover, unlike individual candidates, political parties must ensure that their brands outlast the short-term political impacts of elections, protest movements, and the careers of specific politicians if they are to have long-term influence over public policy. This necessitates ongoing communication between parties and their bases in order to maintain organizational reputations.

With traditional communication channels giving way to social media, researchers can leverage these communication efforts as data to develop an understanding of how political parties encourage their constituents to navigate power structures in the political system of the United States. In doing so, insight can be developed into the distinct differences in language that parties use to promote content within the silos of the political divide, which increasingly caters to the divergent perspectives of their supporters (Jones et al. 2017; Cichocka 2016; Gentzkow, Shaprio, and Taddy 2019; Smith 2019).

When encouraging their followers to pursue electoral and public policy goals, parties use language that innately implies the goal pursuit strategies (i.e., language that implies how goals are pursued) that their followers should use to achieve them. Take, for example, posts written in the language of action (Kanze, Conley, and Higgins 2019), such as a tweet by President Barack Obama encouraging his supporters to be "Fired up! Ready to go!" during his 2012 campaign (Obama 2012). While not outlining a specific call to action for its audience, the content was designed to energize followers to become active participants in his campaign movement, thereby supporting his goal of re-election. Another common form of

content is written in the language of assessment (Kanze, Conley, and Higgins 2019), such as a post written by Obama after he had left office. Here, he encouraged followers to engage in the pursuit of identifying solutions to key policy problems by deliberating on "thought-provoking" (Obama 2019) material about their causes. Subtly using goal pursuit language in social media content is a highly influential strategy for spreading messages within and between the silos of the political divide. This is because the strategies consumers use to pursue goals can be just as important a component for success as the goals themselves (Motyka et al. 2014). But, despite its importance, there is no research to indicate how parties use goal pursuit language to increase the viral strength of social media content within and across the political divide.

This paucity of research on why political posts are shared is a problem for practitioners. Content disseminated by political parties must compete for attention in an environment where voters can simply choose to not consume the information they do not like (Maarek and Wolfsfield 2003). Moreover, there are indicators that voters are generally dissatisfied with existing political communication efforts, as 49% of Americans report feeling worn out by the number of political posts in their feeds (Pew Research Center 2019). In such a congested environment, political parties need to ensure that their content is well-crafted and -targeted in order to be successful. However, existing research on the determinants of content virality does not offer insight beyond existing practice.

For example, empirical work shows that content is more likely to go viral when it is highly emotionally arousing (Berger and Milkman 2012) and occurs between communicators who use similar language and have close ties to each other (Herhausen et al. 2019). But each of these factors are already likely to be present in the content shared between political parties and their constituents. Many of the issues discussed by political parties (i.e., abortion or immigration) are already likely to be highly emotionally arousing for the audience. Political

parties and their constituents are also already likely to use similar language—for example the word "snowflake" being used among conservative representatives and voters. Finally, voters are likely to have long-term ties to a political party (Dalton 2015), with parties already communicating regularly with their constituents. Therefore, given that political communication already bears the hallmarks of successful viral content (Berger and Milkman 2012; Herhausen et al. 2019), the field cannot currently offer insights to political marketers that will enable them to streamline their content more successfully. Moreover, with political communication already crafted in ways that are likely to go viral, why does some political social media content generate more sharing than other content, and how can an examination of such content inform existing research on virality?

We address this knowledge gap by introducing goal pursuit language, referring to language that reflects distinct preferences for goal pursuit strategies identified by regulatory mode theory, as an important and overlooked factor in understanding the sharing of political content on social media. Regulatory mode theory holds that individuals have distinct preferences for goal pursuit strategies, which involve either assessing courses of action (called assessment) or initiating action (called locomotion) toward a goal (Kruglanski et al. 2000). Aligning language to reflect either of these predispositions creates a "regulatory fit" that resonates with individuals. Regulatory fit leads to a sense of "feeling right," which manifests in a range of reactions, such as increased monetary value perceptions (Higgins 2005; Cesario et al. 2008; Conley and Higgins 2018) and intensified judgements of morality (Camacho et al. 2003; Cornwell, Jago, and Higgins 2019). It also results in favorable responses to content (Pierro et al. 2013).

We show that people share political content not just reflective of their goals for engaging in word of mouth (WOM) (Berger 2014), but also based on the strategies for goal pursuit embedded in the language used to craft WOM content. That is, people share content

not just because it fits with the goals they have for engaging in sharing, such as to establish common ground with others (Berger 2014), but also because it fits their preferences for how to engage in goal pursuit more generally. The latter is achieved either through assessment (the evaluation of options and information) or locomotion (the initiation and continuation of action) (Kruglanski et al. 2000). For example, tweets crafted in language that invites the reader to scrutinize a policy would receive more retweets from individuals with high assessment motivations than tweets written in language encouraging followers to take action in support of that policy. On the other hand, tweets written in language that encourages action would receive more shares among Twitter users with high motivations toward locomotion, in comparison with tweets crafted in language inspiring scrutinization of policy. Moreover, we assert that preferences for locomotion language among liberals, and assessment language among conservatives, explains why some political communication content generates more sharing online. In examining this, we identify whether posts crafted in the language of assessment (vs. the language of locomotion) lead to higher retweets.

Building on regulatory fit theory (Avnet and Higgins 2003; Motyka et al. 2014; Higgins and Scholer 2009; Higgins 2005; Cesario et al. 2008; Conley and Higgins 2018), we further show that the sharing of assessment or locomotion language depends on power structures inherent to the system of checks and balances in the U.S. federal government. That is, power possessed by political parties within this system can shape how their audiences engage with goal pursuit language used in their communications, thus affecting whether content is shared. For example, content written in the language of assessment, such as that encouraging readers to question a policy, is less likely to invoke motivations for assessment when posted by parties who have control over successive branches of government. This means that assessment language will be less likely to be shared when it is used by parties in power in the executive branch of government who then also gain power over additional

branches of the legislative. This is because the power possessed by parties who control successive branches of government is better suited to the language of action, as it is commensurate with their role of enacting their political agenda. We further demonstrate that fit between political power and goal pursuit language affects the likelihood that content will be shared.

As will be discussed below, in making these contributions, we consider regulatory mode to expand existing literature on WOM. We do this by first extending past work on how sharing is impacted by the goals consumers have for engaging in WOM (e.g., persuading others) (Berger 2014). We also extend research on how shared language use and closeness between senders and receivers of content can impact sharing (Herhausen et al. 2019). We do this by showing that content posted by political parties is more likely to be retweeted when parties and constituents share preferences for goal pursuit strategies and use similar goal pursuit language in their communication. Last, we introduce the concept of regulatory fit to the field of WOM to provide a theory-driven explanation for why contextual factors— especially concentrations of power—can impact sharing (Berger et al. 2020).

To empirically examine these issues, we use Twitter as our focal social media platform for several reasons. With approximately 22% of Americans using the site (Pew Research Center 2019), Twitter has been demonstrated to help candidates win elections (Kruikemeier 2014; LaMarre and Suzuki-Lambrecht 2013; Bright et al. 2019), for example, by helping to increase vote share (Bright et al. 2019). The platform has also been shown to exert outsized influence over electoral politics, as content posted on Twitter can shape political coverage on other platforms, such as in the traditional news media (Conway et al. 2015; Kreiss 2016; Parmelee 2014), and can also affect opinion leadership among the highly politically interested (Park 2013; Borge and Del Valle 2017). It moreover presents methodological advantages over using comparable sites such as Facebook (Murphy 2017).

Twitter data can be viewed by wide audiences, as well as collected and analyzed on a large

scale, which is not possible on most other social media sites (Murphy 2017).

Conceptual Background

Research on word of mouth (WOM) has identified a number of factors driving

sharing of social media content (Berger 2014; Herhausen et al. 2019). Whether consciously or

unconsciously motivated, individuals are believed to engage in online WOM to facilitate

goals such as impression management, information acquisition, social bonding, emotion

regulation, and persuasion of others (Berger 2014). However, no research has examined how

preferred goal pursuit strategies among senders and receivers of content can impact sharing.

Additionally, empirical work has more recently explored how relationships between

sender and receiver, as well as their shared language use, can drive WOM (Herhausen et al.

2019; Berger 2014). For example, it has recently been demonstrated that linguistic style

matching is important in fostering greater virality in online firestorms (Herhausen et al. 2019;

Berger 2014), as is the tie strength between sender and receiver of WOM content (Herhausen

et al. 2019). However, factors that might foster or reflect the closeness and the linguistic

similarity of groups, such as assessment and locomotion orientations, have not been

investigated by the field. We extend previous work examining how the use of preferred

language among communities, as well as ties between senders and receivers, can drive WOM

by introducing goal pursuit language as a latent factor that underlies the sharing of WOM

content from political parties. Finally, although it is well understood that contextual factors

(e.g., character limits or intended audience) can impact sharing (Berger et al. 2020), the

factors that have been investigated by the field have been disparate, and have often lacked

theory-driven basis for why they can impact sharing (Berger et al. 2020). We therefore

introduce the concept of regulatory fit to the field of WOM to provide theory-driven insight into how the context in which content is sent and received can impact whether it is shared.

Regulatory Mode

Regulatory mode theory proposes that individuals have distinct preferences for the strategies that they use to pursue their goals (Kruglanski et al. 2000). One of these preferences, called assessment, concerns the comparative aspect of goal pursuit, based on choosing the right course of action (Kruglanski et al. 2000). Often conceptualized as a motivation to engage in critical evaluation, assessment orientation is summed up as a desire to "do the right thing" (Kruglanski et al. 2000). Rather than being a normative judgment, this motivation delays decisions in favor of considering other options toward goal attainment. It reflects an individual's reservation toward progress in exchange for greater certainty in a chosen course of action (Kruglanski et al. 2000). For example, consumers who are high on assessment orientation are motivated to pursue goals by comparing between a large assortment of different options so as to ensure they make the best decision about which one they choose (Kruglanski et al. 2000; Avnet and Higgins 2003; Mathmann et al. 2017). Assessment orientation, moreover, orients an individual toward a focus on the past, as when experiencing feelings of nostalgia (Pierro et al. 2013) or fixating on past behavior (Pierro et al. 2018; Pierro et al. 2008; Kruglanski et al. 2018; Webb et al. 2017), thus helping assessors scrutinize options on the path to eventual action (Kruglanski et al. 2010).

The second motivation, called locomotion, relates to a preference for pursuing goals through the initiation of action toward them (Kruglanski et al. 2000). Encapsulated by the Nike slogan "Just Do It," locomotion orientation is an impetus to initiate and sustain uninterrupted movement toward a goal (Kruglanski et al. 2000). This desire for movement is associated with an orientation toward the future (Kruglanski et al. 2016) that often manifests

in positive conceptualizations of change. Locomotors generally demonstrate a positive evaluation of change (Kruglanski et al. 2016), an increased commitment to change (Scholer and Higgins 2012), and a heightened ability to cope with it (Kruglanski et al. 2007).

Further, if a consumer is higher in one orientation than the other, they are said to be predominant in that motivation (Kruglanski et al. 2000). For example, after an instance of interpersonal conflict, individuals predominant in assessment have been found to "dig deeper" into the conflict, thus keeping them from "moving on" (Webb et al. 2017), which would instead be facilitated by a strong predominant locomotion orientation. Within a political context, where communication material is crafted to better enable the strategic pursuit of power, it is important to consider how the use of goal pursuit language can be used to shape the success of political communication.

Regulatory Mode and U.S. Politics

The typical left versus right political divide (Jost 2017), exemplified in the U.S. by the Democratic and Republican parties (Pew Research Centre 2018), may reflect more than just ideology. That is, the divide potentially reflects the preferences of each party's constituents toward different goal pursuit strategies. Progressive ideology, for example, involves a pursuit of social equality that fundamentally necessitates an orientation toward challenging tradition, embracing changes to existing social hierarchies, and initiating action toward generating change (Jost 2017; Jost, Federico, and Napier 2009). For liberals, this action is typically conceptualized as involving the use of big-government initiatives to act on social and economic issues (Jost 2017; Jost, Federico, and Napier 2009; Sullivan 2009). On the other hand, the conservative ideals of upholding tradition and resisting changes to existing hierarchies (Jost 2017; Jost, Federico, and Napier 2009) would necessitate a high level of scrutiny and critical evaluation of any potential changes to existing social structures.

Conservatives, moreover, are typically skeptical of political action, such as that proposed by proponents of liberal ideology, which involve acts of government intervention into markets and the lives of individuals. We therefore conjecture that such motivational distinctions shape preferences for different goal pursuit strategies among constituents of the Democratic and Republican parties. For liberals, their comfort in movement away from the past, acceptance of change to the social hierarchy, and initiation of action to produce that change, would necessitate a strong locomotion orientation. Conservatives, however, have a greater focus on the past (Robinson et al. 2015), which cultivates scrutiny about courses of action designed to foster change to traditional social structures (Jost 2017; Jost, Federico, and Napier 2009). This focus on the past and preference for scrutinizing change would necessitate an orientation toward assessment.

In the age of targeted social media, individuals can follow messaging initiated by their own party in isolation from opposing views (Barbera et al. 2015). Preferences for locomotion or assessment language reflecting the distribution of regulatory mode orientations across the political divide can therefore be revealed through citizens' sharing behaviors. This is because, while political parties may disseminate content crafted with either kind of goal pursuit language, constituents are more likely to use and share the language that resonates with their preferred goal pursuit orientations. Therefore, although individuals crafting or sharing Twitter content are unlikely to be aware of their regulatory mode orientations, the distribution of preferred goal pursuit strategies across the political divide will have consequences for the goal pursuit language used in political communication.

The language of action, which emphasizes the initiation of movement, implies a strategy of moving forward from the past that is less impeded by deliberation. This language of action would therefore be highly reflective of locomotion orientation and would likely resonate with liberals. In contrast, the language of assessment, emphasizing skepticism and

deliberation, implies a strategy of impeding action by choosing instead to spend time on evaluation of alternatives, and would therefore likely resonate with conservatives. Consequently, social media content written in the language of action, which signals locomotion-oriented goal pursuit, will align with the historically progressive stance of the Democratic Party (Sterling, Jost, and Hardin 2019; Blevins 2006) and their liberal constituents. On the other hand, social media content written in assessment-oriented language will align with the conservative ideals of the Republican Party (Gould 2009) and their constituents. Building on the notion that those who favor each type of goal pursuit also share social media messages that align with their party affiliation (Babera et al. 2015), we hypothesize that[1]:

H1a: Tweets originating from the Republican Party (X) are more likely to be predominant in assessment language (vs. locomotion language) (M).

H1b: Mediated by the use of assessment predominant language (M), tweets originating from the Republican Party (X) generate more retweets than tweets from the Democratic Party (Y).

Situational Influences

Regulatory fit is produced when information in the environment, such as a political message, matches a consumer's preferred goal pursuit orientation, leading to increased engagement (Motyka et al. 2014). Regulatory fit can intensify the consumer's evaluation of their goal and goal pursuit process, thereby shaping value perceptions they have for the target of their evaluations. In turn, heightened value perceptions lead to greater engagement in environments that match a consumer's preferred goal pursuit orientation. Accordingly, regulatory fit is not just based on chronic predispositions, but may be created situationally

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[1] [1] Note, the letters X, M, Y, W, Z are used to help identify the key variables in relation to Figure 1.

based on an aspect of the consumer's environment. For example, regulatory fit effects can be induced by watching another person perform a task (Motyka et al. 2014), or through exposure to language in an advertisement (Pierro et al. 2012). Avnet and Higgins (2003) induced regulatory fit via a priming protocol asking consumers to read vignettes containing assessment or locomotion language. Mathmann and colleagues (2017) also used exposure to advertisements featuring assessment language to create a fit effect in consumers, who went on to value choices from larger assortments. Situational inductions of regulatory mode can therefore be induced by environmental cues (Kanze et al. 2020). For example, regulatory mode orientation expressed through a company's mission statement can create an organizationally induced regulatory mode orientation among its employees (Kanze et al. 2020), affecting how they support or avoid instances of company discrimination.

Considering that regulatory fit can be situational and environmental, it is important to consider how the political context experienced by constituents might affect their propensity to share content sent from political parties. Power in the U.S. is distributed between the executive, legislative, and judicial branches of government (Watts 2010), with the different branches of government acting as a check on the power of the others (Watts 2010). For a political party, obtaining the power to advance their political agenda therefore ideally involves gaining control of more than one branch of government. This further means that the agenda of the executive can be significantly constrained by strong opposition in the legislative, and that controlling both the executive and legislative branches of government will significantly increase a party's political power. Given that political content is shared in an environment shaped by this system of checks and balances, we contend that the use of assessment-oriented language is therefore not just a prerogative of conservative ideologies as described in the lead-up to H1, but that its use reflects a deeper symptom of impediments to political action in the U.S. system.

Within this environment, a political party can increase its ability to enact its agenda when it controls successive branches of government. For instance, it would be easier for a sitting Republican president to enact the legislative agenda of the president if the House of Representatives was not held by the Democrats and was instead also held by the Republicans. This would be especially true if the Republicans held both the House of Representatives and the Senate in addition to the White House. Therefore, as a political party gains successive control of multiple branches of government, it has a greater ability to enact policy directly. This would better allow a party to pursue the goal of enacting its legislative agenda in a manner consistent with a locomotion orientation, focused on initiating and sustaining action toward a goal—in this case, the party's political agenda—rather than questioning or delaying action, which would be consistent with an assessment orientation.

Consequently, we contend that the use of assessment-oriented language on social media is moderated by the strength of political opposition that a party faces once it has executive power. This is because political parties with control of the executive will have less need to deploy assessment-oriented language in order to prosecute their political agenda as they gain more power. For example, while a sitting Republican president would refrain from using assessment language in political communication in the White House, if the Republican Party also gained control of additional branches of government, such as winning the House of Representatives, the need to deploy assessment language would be greatly reduced. This is because a party is unlikely to encourage political communication that impedes their own legislative agenda.

These differing concentrations of power would also impact what their supporters would be motivated to share online. Constituents of either party would be less motivated to share content featuring assessment language which would impede political action when their

preferred party had a greater accumulation of power. This is because constituents of a party would also have a reduced motivation to share content questioning and impeding the agenda of a party that they support. For example, with less opposition there would be a greater chance that the legislative agenda being pursued would be commensurate with Republican political goals rather than Democratic political goals that they would be motivated to scrutinize or delay.[2] Motivation to share content featuring assessment language will therefore be reduced among constituents as the party they support gains more power.

Thus, we conjecture that when a party has control over the executive branch of government, an increase in political power experienced by the party lowers impediments to their political agenda and reduces the challenge posed by their opposition. This will diminish regulatory fit in the political environment with assessment language used by the party, and in turn will decrease sharing of content predominant in assessment-oriented language among their audience, leading to fewer retweets for that content. We therefore propose that an increase in political power reduces the positive relationship between the use of assessment-predominant language in political tweets and the increased likelihood of political tweets being retweeted. As such:

H2: The positive relationship between the use of assessment predominant language in political tweets (M), and the increased likelihood of political tweets being retweeted (Y), is

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[2] This would also be the case if there was a Democrat in the White House and Democrats controlling additional Houses of Congress. The Democrats would also find it easier to enact their agenda if they controlled additional levels of government, as potential opposition to their agenda, and consequently their need to use assessment language, would be reduced as they gained more power. Similarly, Democratic constituents would have reduced need for assessment language with Democrats achieving higher concentrations of power. While Republicans still would be more likely to engage with assessment language generally, as indicated in the lead-up to H1, the positive effect of assessment-oriented language in generating retweets would still be reduced as they gained additional dimensions of power. In contrast, as Democrats gain increased political power, their avoidance of assessment-oriented language would be "amplified."

reduced when a party that has control of the executive (Z) gains control of additional legislative branches of government (W).

Importantly, we posit that this will hold regardless of whether the legislative branch of government controlled by the party is measured as the House of Representatives, the Senate, or both houses of Congress combined.

Summarizing the relations suggested in H1 and H2, we arrive at the conceptual model illustrated in Figure 1. In the model, constituents sharing the Republican (vs. Democratic) party tweets favor assessment-oriented language because it shifts attention away from the opposing party's competing orientation toward action. We assert that this resonates with conservative constituents seeking to oppose a progressive political agenda. This role of assessment-oriented language further becomes evident when we consider the level of increased political power possessed by a party sharing assessment-oriented language. With increased political power, the need for considering the opposition is eased, lessening regulatory fit for assessment-oriented language and reducing its effect in political WOM.

< Figure 1 about here >

Methodology

Before presenting our major analyses, we first present a pretest to assess the historical alignment of regulatory mode language among the two major political parties. To do this, we collected the inaugural addresses of all presidents from Franklin Roosevelt in 1933 to Donald Trump in 2016, as the former historical moment is considered to be the point when the two

parties established the constituencies they largely still represent today (Peters n.d.; Chambers and Burnham 1967). Following procedures for operationalizing variables from text, which are detailed below for our main study, the regulatory mode dictionary (Kanze, Conley, and Higgins 2019) was used to measure the regulatory mode language of each inaugural address. A t-test was then conducted to determine differences in regulatory mode language between parties. Supporting our historical conceptualizations of the two major parties, the GOP (M = 9.9, SD = 6.95) was found to have a higher mean proportion of assessment-predominant language than the Democrats (M = 4.25, SD = 5.68), with the difference between the two reaching significance (t (17) = 2.061, p < .05).

Main Study

In this section we now describe our research method for our main study, which involved data collection, text preprocessing, operationalization of variables, summary statistics and correlations, data analysis, and corrections for endogeneity. We also report an additional study to replicate our findings. In the following sections, we detail each step of the process and explain how the unstructured textual data was first converted into measures of predominant regulatory mode orientations.

Data Collection

The first step involved collecting the data. To do this, we collected all tweets originating from the official Twitter handles of the Democratic and Republican parties (@TheDemocrats and @GOP). We downloaded all tweets disseminated by both parties from the time of their Twitter handle creation (December 2007 for @GOP and April 2008 for @TheDemocrats) until the time of our data collection in September 2019. This resulted in a rich corpus of 55,560 tweets, combining data from both handles for the 12-year period

(December 2007 to September 2019), which we use in our main study. Separately, we also collected tweets from the two handles for the period between October 2019 and June 2020, which we use in our replication study below. Although Twitter data have limitations, Twitter has been shown to be a rich source of data for marketing research (Murphy 2017; Berger et al. 2020). Among all social media platforms, the variables available in a Twitter dataset are far more amenable to answering questions of wider research interest. In addition, Twitter's data access policies through its Application Programming Interface (API) are more suited for open-platform data sources.

As part of this method, we used web crawling techniques to download data from online websites (Berger et al. 2020). While popular statistical software like SAS has such functionalities available, more complex data requirements, such as the one in this paper, require customized coding in open-source languages. To download the tweets required for this paper, we wrote specialized Python code to retrieve the Twitter data. We first searched for all the tweets that originated from the handles of the two parties using the search functionality in the Twitter API and recorded the unique identifier for each tweet that the search results returned. We then used the *tweepy* package in Python (Roesslein 2020) to extract the following data from the more than one hundred variables that Twitter API returns for a tweet:

- *Created_at* – provides the date and time the tweet was created

- *Retweet_count* – number of times the tweet was retweeted (or shared) by the readers

- *Text* – the actual text of the tweet

Text Preprocessing

In accordance with best practice methods for this technique (Berger et al 2020), we preprocessed the data. Text data extracted from Twitter using the method described above contains alphanumeric characters, special symbols (such as hash-tags), URLs, and ASCII

characters. These need to be removed from the tweets in order to achieve high quality results. This preprocessing step uses NLP procedures that clean and transform the data into machine-friendly formats (Bird, Klein, and Loper 2009; Manning and Schütze 1999). The text then needs to be tokenized (fragmented into words or phrases), lemmatized (retaining the base form of the token) and tagged (Pustejovsky and Stubbs 2012). In addition, certain common words, also known as stop words (Berger et al. 2010)—like "the," "in," "and," and "with"—need to be filtered. In our case, stop words were filtered as they would not provide valuable insight for our research. We used a combination of code in Python and R to perform these tokenization and tagging steps. We performed the lemmatization step at a later stage after filtering the tokens, as described in the next section. These steps provided us with a matrix with a frequency count of tokens in each of the tweets, commonly referred to as the Document Term Matrix (DTM). At this stage, we were left with 7213 unique tokens across the 55,560 tweets.

Operationalizing Variables from Text

We operationalized the regulatory mode variables using the cleaned DTM and the regulatory mode dictionary provided by Kanze, Conley, and Higgins (2019). Kanze, Conley, and Higgins (2019) proposed and validated a regulatory mode dictionary which they used to perform a linguistic analysis of organization mission statements to determine the degree of *locomotion* vs. *assessment* language used in the statements. One advantage of this dictionary is that it provides the root of the token (for example, *urg*, which accounts for all forms of the word including, but not limited to, *urgency*, *urgent*, *urgently*, etc.). We then used the *stemDocument* function in the *tm* package in R (Feinerer 2019) to retain only the regulatory mode tokens. This filtering left us with a DTM with 913 unique tokens across 55,560 tweets.

In order to adjust for the length of the tweets in our data, we operationalize the *Assessment Predominant Regulatory Mode Orientation (APL)* as follows:

$$APL = \text{Assessment Orientation} - \text{Locomotion Orientation}$$

Where:

$$\text{Locomotion Orientation} = \frac{\text{Number of locomotion–focused words in the tweet}}{\text{Number of words in the tweet}}$$

$$\text{Assessment Orientation} = \frac{\text{Number of assessment–focussed words in the tweet}}{\text{Number of words in the tweet}}$$

Operationalizing the Variables for Legislative and Executive Power

The moderating variables in our model are categorial variables indicating "Y" if the variable definition is satisfied and "N" if it is not. The executive power variable, as described in Table 1, is coded as "Y" if the tweet originates from the president's party. For example, if a tweet is between January 20, 2009 and January 20, 2017 and originates from the Democratic Party's handle, this variable is coded as "Y." However, during this time period, all tweets that originate from the Republican Party's handle are coded as "N." The categorical variables for legislative power are coded in a similar manner. The categorial variable indicating the party in control of the House of Representatives is coded as "Y" if the tweet is from the party that controlled it and "N" otherwise, whereas the categorial variable indicating the party in control of the Senate is coded as "Y" if the tweet is from the party that controlled it and "N" otherwise. The categorical variable indicating the party in control of Congress is coded as "Y" if the party from which the tweet originates controlled both the Senate and the House of Representatives, and is coded as "N" otherwise. The correlations among the variables which we report in Table 2 and describe below also provide a count of the number of tweets in each condition.

<Insert Table 2 about here>

Summary Statistics and Correlations

We show some examples of tweets scoring high (and low) on APL for both party handles and highlight differences in the number of retweets they garner. The two tweets below include an assessment-predominant word (true, truth) and score highly on APL. However, the tweet from the Republican handle is retweeted more (26 retweets) than the tweet from the Democratic handle (18 retweets).

> *Republicans: As Senate Dems consider a budget for the first time in years, will the American people see their **true** colors?*

> *Democrats: The **truth** is that as the immigration reform debate continues, Republicans show their **true** colors.*

At the same time, when we consider the two tweets below, which include a locomotion-predominant word (lead) and score low on APL, the tweet from the Republican handle is tweeted less (51 retweets) in comparison to the tweet from the Democratic handle (156 retweets).

> *Republicans: If Dems cannot **lead** their own party how can they **lead** America?*

> *Democrats: Democrats **lead** with our values that's why we launched the Demsforyou service program. Click here to find out more.*

Table 1 provides the summary statistics for the variables used in the analysis. We also find that the total number of tweets per month (GOP (M = 9.186, SD = 8.920); DEM (M = 6.925, SD = 6.732); t(6,365) = 11.723, p < .001), retweet count (GOP (M = 237.490, SD = 678.948); DEM (M = 148.808, SD = 361.195); t(50,051) = 19.796, p < .001), and the APL (GOP (M = .004, SD = .394); DEM (M = -0.047, SD = .464); t(47,103) = 13.729, p < .001) significantly differ between the Democrats and the Republicans, whereas the length of the tweet itself does not (GOP (M = 7.117, SD = 2.468); DEM (M = 7.089, SD = 2.542); t(51,093) = 1.285, p = .1988). This indicates that while there is no significant difference in

message length, tweets originating from the Republican Party are predominant in assessment language, thus supporting H1a.

<Insert Table 1 about here>

Next, we examine the correlations between the variables. These are reported in Table 2. Since some of our variables of interest are categorical (yes/no), we first report the correlations for all variables. In addition, for further detail, we report these correlations for the continuous variables in the groups formed by each of these categorical variables. The overall correlation (for all 55,560 tweets) between the retweet count and the assessment-predominant regulatory mode orientation (APL) is not significant ($r = .0034$). However, when considering the coefficients split by the party from whose handle the tweet originates, the correlation coefficient is significant for both Democrats ($r = .0026$, $p < .05$) and Republicans ($r = -0.0128$, $p < .05$). This correlation coefficient also shows differences in significance when the tweet is from the President's party, the party that controls the House of Representatives, the party that controls the Senate, and the party that controls Congress. These observed variations motivate the proceeding formal tests of our conceptual model, which we report below.

<Insert Table 2 about here>

Data Analysis

We test the conceptual model proposed in Figure 1 in multiple steps. The first analyses check for the mediation effect of APL on retweets. In our subsequent analyses, we

include the moderation effects as a result of executive power (i.e., when the sitting president belonged to the party from which the tweet was sent), and for legislative power (i.e., when the House of Representatives, the Senate, and/or both houses of Congress were controlled by the party from which the tweet was sent). For all models, we standardize the continuous variables and include control variables to account for the year fixed effects. These control variables capture the influence of aggregate trends and help eliminate omitted variable bias caused by excluding unobserved variables that evolve over time but are constant across tweets for a particular year. We report the results and findings from each of these analyses.

First, we consider the results of two multiple regression models. Model 1 tests the main effect for the tweet's originating handle (Republicans vs. Democrats) on APL (i.e., assessment-predominant vs locomotion-predominant language). The results are reported in Table 3. Strengthening support of H1a, and in support of H1b, Model 1 shows a significant effect of the tweet originating from the Republican handle on APL ($\beta = .118$, $p < .001$) and that APL has a marginally significant effect on the number of retweets ($\beta = .005$, $p < .1$). In addition, there is also a significant direct effect of the tweet originating from the Republican handle on the number of retweets ($\beta = .158$, $p < .001$), indicating a partial mediation through APL. We also bootstrap to estimate the indirect effect of the mediation as suggested by Hayes (2018, p.p 585) and find a significant indirect effect ($\beta = .001$, $p < .1$). This supports H1b, showing that tweets originating from the Republican Party, mediated by assessment-predominant language, generate more retweets than tweets originating from the Democratic Party.

<Insert Table 3 about here>

Next, we check for the moderating effects of political power on this relationship. We test for both the effects of executive power (i.e., tweets originating from the President's party) and legislative power (i.e., tweets originating from the party that controls the House of Representatives, the Senate, and/or both houses of Congress combined). First, in Model 4, when we consider the interaction effects of executive power in the presence of interaction with legislative power (measured as the tweet originating from the party that controls the Senate), we find that executive power (β = -.036, $p < .01$) and legislative power (β = -.033, $p < .05$) both reduce the main effect of APL on retweets observed in Model 1. Further, the bootstrapped indirect effect (β = .013, $p < .1$), while accounting for the three-way interaction (β = .057, $p < .001$), is marginally significant. Also accounting for the three-way interaction, the bootstrapped indirect effect for Model 6, where legislative power is measured as the tweet originates from the party that controls the House of Representatives (β = .022, $p < .05$), and for Model 8, where legislative power is measured as the tweet originates from party that controls both houses of Congress (β = .029, $p < .05$), are both significant. Thus, the positive effect of assessment-predominant language on generating retweets is reduced as parties gain control over successive branches of government, thus demonstrating support for H2.

Importantly, as can be seen in Table 4 which reports the interactions along with the confidence intervals, for Model 2 we find that the interaction effect of executive power (β = -0.007) with the main effect of APL on retweets observed in Model 1 is not significant. In Models 3, 5, and 7, we also find that the interaction effect of legislative power, measured as the tweet originating from the party that controls the Senate (β = -0.001), the House of Representatives (β = .015, $p < .1$), and Congress (β = .010), with the main effect of APL on retweets is not significant (or marginally significant for Model 5) in each model. This further demonstrates support for H2, showing that the positive affect of APL on reducing retweets does not occur when a political party obtains control of only one branch of government, but

that parties need to experience an increase in political power involving successive branches of legislative government beyond the executive before the effect of APL on increasing retweets is reduced. We graphically represent these three-way interactions in Figure 2. Here we can observe that the effect of APL on increasing retweets is reduced when the party that is tweeting has control of both the executive and legislative branches of government, and that this occurs irrespective of which branch of legislative government is controlled by the party.

<Insert Table 4 about here>

<Insert Figure 2 about here>

Endogeneity Correction

The previous models are built on standard premises in mediation analyses and estimated using seemingly unrelated regressions. The interpretations of the parameters in these models assume that the error terms in the outcome equation and the mediator equation are not correlated (Shaver 2005). However, this assumption is likely to be violated since managers of Twitter accounts would deliberately use language that garners maximum reach (retweets and favorites). Our previous models include the time fixed effects, which capture the influence of aggregate trends. This helps eliminate omitted variable bias caused by excluding unobserved variables that evolve over time but are constant across tweets for a particular year. However, the strategic behavior of social media managers can create endogeneity of the language used and lead to violations of the required assumptions in standard mediation analyses.

In this study, we use the latent instrument variable (LIV) approach (Ebbes et al. 2005), which introduces a binary unobserved instrumental variable that partitions the endogenous predictor (i.e., the mediator variable capturing the predominant regulatory mode

orientation) into two components: one uncorrelated and the other correlated with the error term in the main equation (in this case, the retweet count model). We note that the Shapiro-Wilk's test for normality, conducted on samples of 2000 observations randomly drawn from the total of 55,560 of the endogenous regressor (APL), confirms the non-normality ($p < 0.001$). This validates the use of the LIV approach (Papies et al. 2017). We implement the Bayesian adaptation of this method used by Zhang, Wedel, and Pieters (2009) to account for the endogeneity introduced by the language used in the tweets in our models.

We find that the endogeneity correction using the LIV approach does not change the conclusions of our analysis. However, we find that when they are corrected for bias using the LIV approach, the coefficients are larger than the ones we report in Table 4. Hence, the coefficients reported in Table 4 are conservative estimates of the bias corrected coefficients. We also find that the LIV component correlated with the error term in the main equation is insignificant and conclude that the endogeneity in the model has been addressed. We explain the Bayesian model and its estimation along with its results, and a sample code in OpenBUGS (Lunn et al. 2009), in the Web Appendix.

Replication Study

In order to demonstrate replication of the results we present above, we now report findings from a study conducted on an additional sample of 5012 tweets from the Democratic and Republican Party Twitter accounts for the period between October 2019 and June 2020. This method is in line with best practice methods for conducting replications (Simmons et al. 2011), as it allows for the provision of an exact, rather than conceptual, replication of our findings. Importantly, as the study was conducted after the first submission of this manuscript for peer review, it further separates exploratory hypothesis generation and confirmatory testing of hypotheses (Nosek et al. 2018). We achieve these ends by collecting additional

tweets from the focal Twitter handles (@GOP and @TheDemocrats) for the period between October 2019 and June 2020 and use this data for prediction.

Therefore, to begin, we collect all additional tweets and follow the text cleaning procedures described above to calculate the desired variables. We first check for the difference in APL and find that H1a continues to be supported (GOP (M = -0.018, SD = .037); DEM (M = -0.016, SD = .044); t(2,512) = -1.572, p = .06). Although we cannot use this new data to replicate the entire study, as our moderating variables for executive power and legislative power do not change during this period, we run Models 4, 6, and 8 on the original data to predict the retweet count for the new data collected. We find that when legislative power is measured as tweets from the party that controls the Senate, the predicted value for retweets (M = -0.143, SD = .011) is not only in the same direction as that of the actual value for retweets (M = -0.001, SD = .014), but the two means are also not statistically different (t(5011) = 8.9805, p < .001). We find similar results when the legislative power is measured as tweets from the party that controls the House of Representatives (Predicted (M = -0.164, SD = .012); Actual (M = -0.001, SD = .014); t(5011) = 10.067, p < .001) and when the legislative power is measured as tweets from the party that controls Congress (Predicted (M = -0.174, SD = .013); Actual (M = -0.001, SD = .014); t(5011) = 10.587, p < .001). These findings establish a replication of the results we present above for our main sample.

General Discussion

As part of the growing effort to understand the role of social media in influencing public policy debate in western democracies (Lazer et al. 2018; Wardle and Derakhshan 2017), we use 55,560 Tweets from the official Twitter accounts of the Democratic and Republican parties to examine how goal pursuit language influences retweets. We hereby

contribute broadly to the literature on drivers of WOM by showing that sharing information on social media goes beyond established factors (Berger 2014) such as impression management or persuading others. Instead, an understanding of WOM needs to account for the preferred goal pursuit strategies of WOM recipients. We demonstrate that Twitter messages are more likely to be shared when the language expressing goal pursuit aligns with the political motivations of the audience.

We further argue that goal pursuit language resonates differently with Democrats and Republicans because their political agendas differ in regard to social progress. Specifically, Republicans are more likely to share tweets predominant in the language of assessment because deliberation shifts attention away from action. This aligns with a conservative ideology of restraining the progressive action typically advocated for by the Democrats.

However, while the influence of goal pursuit language indeed clusters within the silos of the political divide, we note that political power further shapes how a party's constituents relate to the goal pursuit language the party uses. Specifically, we show that gaining power can reduce the role of assessment-oriented language on the sharing of political content. Our interpretation is that with fewer political impediments to their political agenda, constituents become motivated to achieve their political agenda directly. While we observe this effect across Republican and Democratic party tweets, it highlights the divergence of their political agendas. That is, Republicans are more likely to share assessment-oriented language, but as their party gains political power, the effect of assessment-oriented language is reduced. In contrast, as Democrats gain political power, their avoidance of assessment-oriented language is amplified.

Together, our contributions show that when crafting social media content, political parties should consider the impacts of goal pursuit strategies, which have so far been unexplored by the WOM literature. In designing content, parties should consider how the

language used to deliver a political message frames goal pursuit for their audience. This is important, as audiences are likely to have varied responses to locomotion or assessment-oriented language used in their content. Further, by considering the extent of their political power, they can better predict how audiences will respond to their content. These contributions raise important public policy implications and provide interesting avenues for future research that should be explored. We discuss these below.

Public Policy Implications

Our findings imply that bridging political divides is essential, as it demonstrates that Republican and Democratic constituents speak different goal pursuit languages when sharing ideas on social media. A simple prescription for public policy makers in encouraging greater dialogue between opposing political sides is to learn to speak the preferred goal pursuit language of their opposition. Regulatory mode theory is well established, and dictionaries of goal pursuit language are freely available (Higgins Lab 2019; Kanze, Conley, and Higgins 2019). This renders regulatory mode language a concrete tool to use in order to reduce the alienation of political opponents on social media, which our work shows to be likely occurring, at least in part, because of how messages are communicated.

When encouraging political discourse by speaking each other's language, public policy makers also need to consider the effect of power on the sharing of content within political systems. There are increasing efforts to educate the public about how content circulates on social media (News Literacy Project 2020). It is important to adapt the focus of such education to ensure the public understands that parties without executive power have a normative democratic function in holding governments to account by scrutinizing their policies (Norton 2008), and that the U.S. political system is designed so that legislative and

executive branches of government act as a check on the power of the other (Watts 2010). It is therefore critical that individuals are educated to understand that parties who hold executive power will realistically seek to undermine the ability of their opposition to impede their political agenda.

We find that assessment-oriented language, which is the natural language of debate, will spread further when used by parties who do not control successive branches of government. This shows that all parties have a role in contributing to public policy debates, and that their ability to contribute to these debates must be safeguarded even when there are strong power differences between them. For example, education of the public about social media should oppose urges by governing parties to paint credible opposition to their policies as illegitimate. Additionally, considering that debate content is likely to spread further when it originates from parties who do not control successive branches of government, stakeholders (i.e., the press and judiciary) need to ensure that all parties are able to access high-quality information on policy issues. For example, strong Freedom of Information laws need to be maintained within democracies (Berliner 2014), and bi-partisan congressional committees should provide parties with public policy detail to ensure robust debate.

Recommendations for Future Research

While our work here presents these practical implications for public policy, further research should be conducted to examine specific approaches to the interventions we have proposed. For example, work should be conducted to examine the impact of educating liberal and conservative social media users on their preferences for goal pursuit language. Research should first evaluate what political actors should conduct these campaigns. Consumers will likely react differently to programs highlighting the power of goal pursuit language when

they originate from government departments, political parties, or social media platforms themselves.

Particular consideration should be given to the role of social media companies in these efforts. Companies like Facebook and Twitter are increasingly confronting the necessity of developing solutions to discourage the spread of disinformation on their platforms (Facebook n.d.; Harrison 2019). Despite these efforts, they still face substantial criticism that their solutions have not been effective enough for the sector to avoid policy intervention (Tusikov and Haggart 2019). Research should explore whether social media companies could successfully adopt programs that build awareness of goal pursuit language as part of these initiatives. Particularly, it must be established whether users are still more likely to share content crafted with their preferred goal pursuit language when they have been informed about how persuasive such content is likely to be. It is highly likely that individuals will judge their own communications as less persuasive when crafted in the goal pursuit language of their opposition. This may be particularly pronounced for individuals who identify strongly as liberal or conservative and are often prone to making up a significant proportion of the prospective talent pool for governments and political parties. Research should therefore be conducted to explore how this might demotivate practitioners from adopting a specific goal pursuit language, and identify methods to correct and overcome any potential demotivation that practitioners might experience.

Additionally, given that the effect of assessment-predominant language is reduced as political parties gain control of successive branches of government, further research should be conducted to examine whether the effect of assessment-oriented language on sharing is similarly reduced by other forms of power. Specifically, research should examine whether the effect of assessment-oriented language on sharing is impacted when the origin is from

independent agencies of the U.S. Government, such as the Environmental Protection Agency or Securities and Exchange Commission.

Lastly, in examining how successive increases in power attained by a political party affects the sharing of regulatory mode language, we have theorized that reduced impediments to action for the executive also reduces regulatory fit for assessment-oriented language, thereby decreasing sharing of assessment-oriented language. Therefore, in order to examine how opposition to an agenda shapes communication concerning it, we have necessarily focused our theorizing on situations where parties have the ability to dominate the political agenda through first controlling the executive branch of government (i.e. the presidency). This imposes a limitation on our research, as it means that we offer limited insight into how regulatory mode language impacts sharing of content from parties with control over the legislative but not the executive. Our insights are further limited regarding communication from parties who control neither the executive or legislative branches of government. Future research should consequently seek to answer questions of how power concerning the checks and balances inherent to the US political system would affect communication by parties who do not control the executive and therefore do not set the political agenda to begin with.

This research is likely to be highly relevant to modern political communication scholarship as there have been notable moments in recent history where one party has swept control over the executive and both branches of the legislative at the same time. Further, voters are increasingly registering support for third parties (Reinhart 2018), who by their nature must find ways of communicating with voters without control of either the executive or legislative government. Considering that power within a system of checks and balances has been found to affect content virality, it would be an interesting extension of the work presented here to explore differences in communication and virality when parties have no

control whatsoever over the political system. While we offer limited insight into them, a speculative discussion concerning these issues can be found in the web appendix.

Finally, there are several avenues that future research could pursue in order to expand on the theoretical work presented here. First, future research could examine whether goal pursuit language might have different potency in affecting the sharing of content based on the different goals that individuals have for engaging in WOM (Berger 2014). For example, could goal pursuit language impact sharing differently when individuals are engaging in WOM to establish common ground, versus when they are sharing in order to persuade others? Second, work on this topic could also look at virality from the perspective of regulatory focus theory, which examines whether individuals are motivated to seek vigilant or aspirational goals (Higgins 1998). By extending the existing regulatory focus dictionary (Kanze, Conley, and Higgins 2019) to enable analysis of short-form content such as tweets, researchers could also examine the effects of regulatory focus on sharing, and of any potential additive impacts of regulatory fit between regulatory mode and regulatory focus language in Twitter content (Cornwell, Franks, and Higgins 2019; Higgins, Nakkawita, and Cornwell 2020). Particularly, such analyses could be used to investigate whether parties use locomotion language in the service of changing the status quo or whether they use it in order to maintain it.

Further, considering that there is a tendency to avoid contact with opposing views on twitter, motivations for the use of preferred regulatory mode language may be more extreme on Twitter than they would be on other platforms. Future research should examine regulatory mode usage in political speech on mediums aimed at a more general audience in comparison to content on mediums with more partisan audiences.

Conclusion

Using 55,560 tweets from the official Twitter accounts of the Democratic and Republican parties in the U.S., we offer a window of insight into the approaches that political parties use to encourage sharing of their content within the contemporary political divide. Specifically, we show that tweets sent by the Republican Party are more likely to be predominant in the language of assessment (as opposed to the language of locomotion). We further find that while tweets predominant in the language of assessment lead to more retweets for Republicans, this effect is reduced as political parties gain control of successive branches of government. This is because successive increases in political power create fewer impediments toward implementing a party's political agenda. As impediments to action are reduced, so is regulatory fit for assessment-oriented language. In this way, goal pursuit language shared on Twitter reveals distinct approaches to obtaining and dealing with power across the U.S. political system. Goal pursuit language therefore presents an important tool for political parties and public policy makers to successfully conduct policy debates in the future.

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				Republicans		Democrats	
Variable	**Description**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Monthly Tweet Count	Total number of tweets (per month)	8.062	7.973	9.186	8.920	6.925	6.732
	t-test		$t(6,365) = 11.723, p < 0.001$				
Retweet Count	Number of times the tweet was retweeted	199.000	565.200	237.490	678.948	148.808	361.195
	t-test		$t(50,051) = 19.796, p < 0.001$				
APL	Assessment Predominant Regulatory Mode Orientation (difference between Assessment and Locomotion word counts in the tweet)	-0.018	0.427	0.004	0.394	-0.047	0.464
	t-test		$t(47,103) = 13.729, p < 0.001$				
Tweet Length	Length of the tweet	7.105	2.500	7.117	2.468	7.089	2.542
	t-test		$t(51,093) = 1.285, p = 0.1988$				

Independent Variable

Who Tweets? (Rep = Y) Variable indicating Y if the tweet originates from the GOP handle

Moderator Variables

Executive Power Variable indicating Y if the tweet originates from the handle of the President's Party

Legislative Power

    THOR Control Variable indicating Y if tweet originates from the handle of the party controlling The House of Representatives

    Senate Control Variable indicating Y if tweet originates from the handle of the party controlling the Senate

    Congress Control Variable indicating Y if tweet originates from the handle of the party that controls both THOR and Senate

Table 1: Variable Description and Summary Statistics

<div align="center">**(n = 55,560)**</div>

	Retweet Count	Favorites Count	Tweet Length	APL	Who Tweets?	Executive Power	THOR Control	Senate Control	Congress Control
Retweet Count	1								
Favorites Count	0.9123*	1							
Tweet Length	-0.0191*	-0.0223*	1						
APL	0.0034	0.0001	-0.0190*	1					
Who Tweets?	0.0650*	0.1113*	-0.0027	0.0601*	1				
Executive Power	0.1759*	0.1893*	-0.0710*	-0.0480*	-0.4968*	1			
THOR Control	-0.0434*	-0.0190*	-0.0483*	-0.0067	0.4617*	-0.2599*	1		
Senate Control	0.1181*	0.1540*	-0.0965*	-0.0126*	0.3537*	0.1415*	0.2618*	1	
Congress Control	0.0730*	0.0891*	-0.0916*	0.005	0.4193*	-0.0453*	0.6492*	0.7123*	1

[†]Significant at the 10% level. *Significant at 5% level.   **Significant at 1% level.   ***Significant at the .1% level.

Table 2. Correlations between the variables

DV = Assessment Predominant Regulatory Mode Orientation Language (APL)	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Constant	-0.183† (0.096)	-0.183† (0.096)	-0.183† (0.096)	-0.183† (0.096)	-0.183† (0.096)	-0.183† (0.096)	-0.183† (0.096)	-0.183† (0.096)
Who Tweets? (Republicans = Y, Democrats = N)	0.118*** (0.009)	0.118*** (0.009)	0.118*** (0.009)	0.118*** (0.009)	0.118*** (0.009)	0.118*** (0.009)	0.118*** (0.009)	0.118*** (0.009)
DV = Retweet Count								
Constant	-0.509*** (0.088)	-1.190*** (0.087)	-0.448*** (0.272)	-1.381*** (0.087)	-0.591*** (0.088)	-1.300*** (0.087)	-0.487*** (0.088)	-1.337*** (0.087)
Who Tweets? (Republicans = Y, Democrats = N)	0.158*** (0.008)	0.377*** (0.009)	0.093*** (0.008)	0.396*** (0.010)	0.238*** (0.009)	0.430*** (0.009)	0.135*** (0.009)	0.404*** (0.010)
Assessment Predominant Regulatory Mode Orientation Language (APL)	0.005† (0.004)	0.012* (0.005)	0.009† (0.005)	0.026*** (0.006)	-0.005 (0.005)	0.015* (0.007)	0.003 (0.005)	0.021*** (0.006)
Executive Power (Y = Tweet from President's Party Handle)		0.462*** (0.009)		0.632*** (0.013)		0.518*** (0.013)		0.580*** (0.011)
Legislative Power (Senate Control, Y = Tweet from Party Handle controlling the Senate)			0.175*** (0.008)	0.146*** (0.009)				
Legislative Power (THOR Control, Y = Tweet from Party Handle controlling The House of Representatives)					-0.181*** (0.009)	-0.076*** (0.013)		
Legislative Power (Congress Control, Y = Tweet from Party Handle controlling the Congress)							0.060*** (0.009)	0.129*** (0.012)
Interaction Effects								
APL x Executive Power		-0.007 (0.008)		-0.036** (0.011)		-0.021* (0.010)		-0.027** (0.009)
APL x Legislative Power (Senate Control)			-0.001 (0.008)	-0.033* (0.011)				
APL x Legislative Power (THOR Control)					0.015† (0.008)	-0.013 (0.010)		
APL x Legislative Power (Congress Control)							0.010 (0.009)	-0.031* (0.012)
APL x Executive Power x Legislative Power				0.057*** (0.016)		0.042** (0.015)		0.065*** (0.017)
Bootstrapped Indirect Effects (with 5000 repetitions)								
Who Tweets →APL → Retweet Count	0.001† (0.001)	0.001 (0.001)	0.001 (0.001)	0.013† (0.007)	0.002* (0.001)	0.022* (0.010)	0.001 (0.001)	0.029* (0.010)

†Significant at the 10% level.   *Significant at 5% level.   **Significant at 1% level. ***Significant at the .1% level.

Table 3. Mediating effects of APL on Retweets moderated by the Executive Power and Legislative Power

Model	Interaction	Coefficient	SE	95% Confidence Interval	
				LL	UL
2	APL x Executive Power	-0.007	0.008	-0.022	0.008
3	APL x Legislative Power (Senate Control)	-0.001	0.008	-0.016	0.014
4	APL x Executive Power	**-0.036**	**0.011**	**-0.056**	**-0.015**
	APL x Legislative Power (Senate Control)	**-0.034**	**0.011**	**-0.056**	**-0.011**
	APL x Executive Power x Legislative Power	**0.057**	**0.016**	**0.025**	**0.088**
5	APL x Legislative Power (THOR Control)	0.015	0.008	0.000	0.030
6	APL x Executive Power	**-0.021**	**0.010**	**-0.041**	**-0.002**
	APL x Legislative Power (THOR Control)	-0.013	0.010	-0.033	0.007
	APL x Executive Power x Legislative Power	**0.042**	**0.015**	**0.012**	**0.072**
7	APL x Legislative Power (Congress Control)	0.010	0.009	-0.007	0.027
8	APL x Executive Power	**-0.027**	**0.009**	**-0.044**	**-0.009**
	APL x Legislative Power (Congress Control)	**-0.031**	**0.012**	**-0.054**	**-0.007**
	APL x Executive Power x Legislative Power	**0.065**	**0.017**	**0.032**	**0.099**

Note: Numbers in bold are significant at 95%

Table 4. Confidence Intervals for Interactions

Z

Executive Power

Legislative Power   W

Dem/Rep
Rep = Y   Assessment Predominant Regulatory
Mode Orientation   Retweet Count
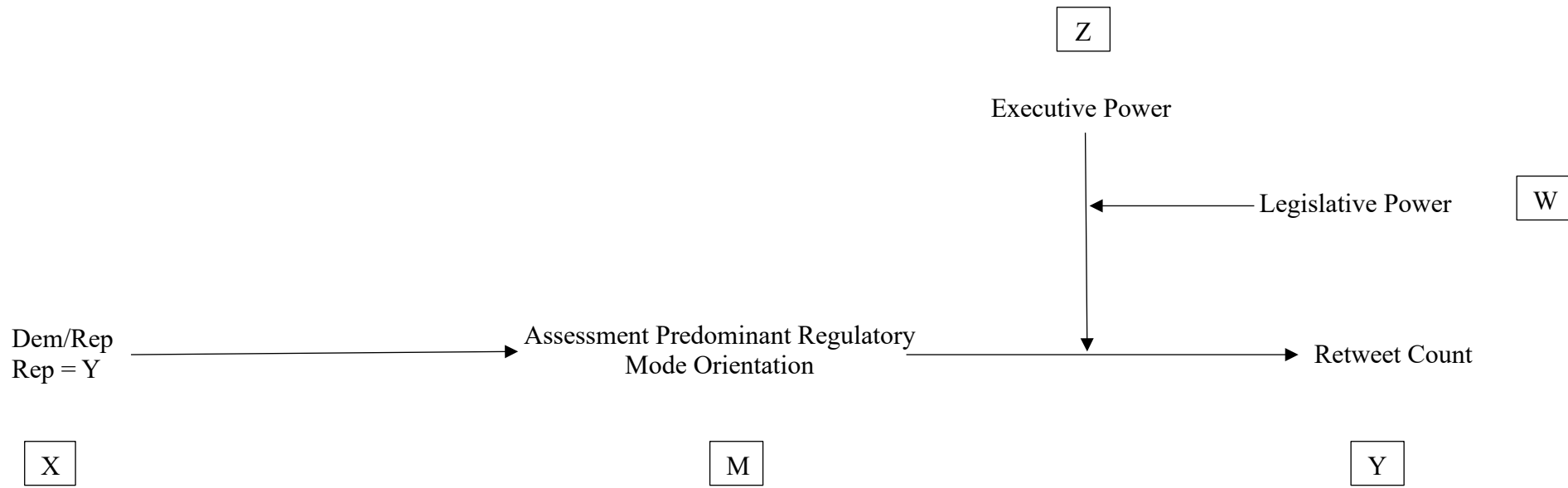
X   M   Y

Figure 1. Conceptual Model
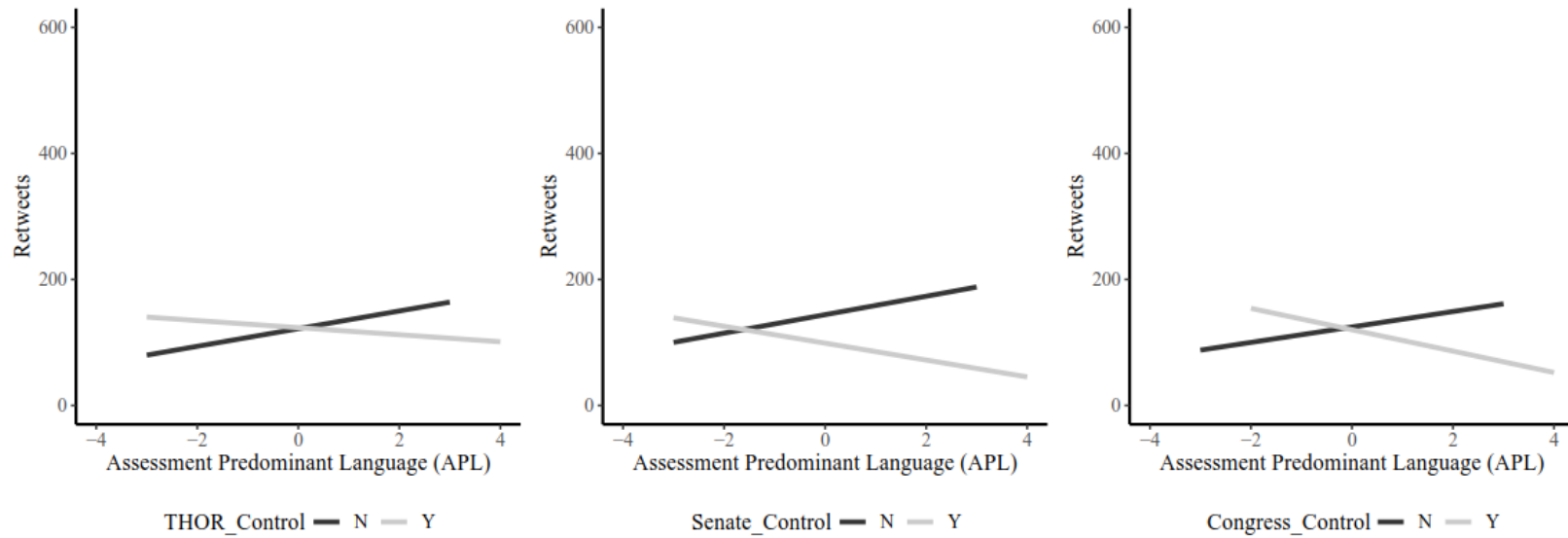
Figure 2. Effect of APL on Retweets When the Party Controlling the Executive Controls Branches of the Legislative

Power and the Tweet: How Viral Messaging Conveys Political Advantage

Bayesian Estimation of the Moderated Mediation Model accommodating for Endogeneity in the Moderator

In this web appendix, we first restate our generalized moderated mediation model followed by estimations of a Bayesian version of it. In this model, we also show the latent instrumental variable (LIV) for the mediator to accommodate for the endogeneity (Ebbes et al. 2005; Rutz, Bucklin, and Sonnier 2012; Wang and Preacher 2015; Zhang, Wedel, and Pieters 2009). We apply the Bayesian statistical framework because it allows for computation of standard errors of the indirect effects in a straightforward manner (Zhang, Wedel, and Pieters; 2009).

In figure WA1, below we represent a generalized moderated mediation model where X is our independent variable, Y is the dependent variable, M is the mediator, and Z and W are the moderator variables. We also show that the mediator M, is instrumented using a latent instrumental variable (LIV) to accommodate the endogeneity. The model also includes control variables.
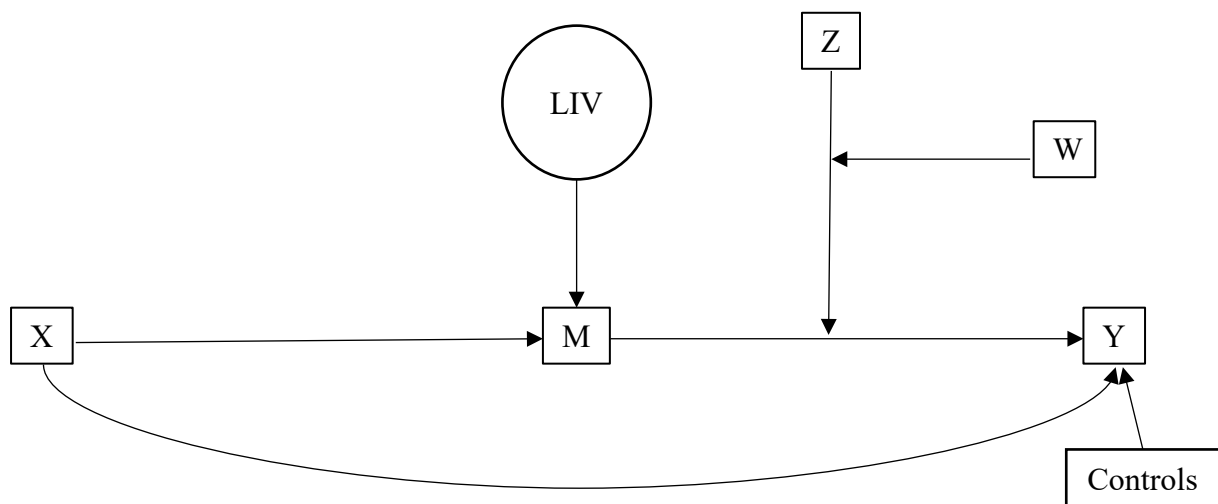

Figure WA1. Moderated Mediation Model with a Latent Instrument for the Mediator

These variables in our case are as follows:
X: Variable indicating who tweets (coded as 1 for tweet from the GOP handle, else 0)
Y: Total number of retweets
M: Assessment Predominant Regulatory Mode Orientation Language (APL)
Z: Executive Power (coded as 1 for tweet from the President's party, else 0)
W: Legislative Power (three different operationalizations used)
    THOR Control (coded as 1 for tweet from the party controlling The House of Representatives, else 0)
    Senate Control (coded as 1 for tweet from the party controlling the Senate, else 0)
    Congress Control (coded as 1 for tweet from party controlling both houses, else 0)
Controls: Year dummies (to capture the year specific effects)

Next, we specify the moderated mediation model with control variables but without the latent instrument variable for the mediator.

(1a) $$y_i = \beta_0 + \beta_1 m_i + \beta_2 m_i z_i + \beta_3 m_i w_i + \beta_3 m_i w_i z_i + \gamma_1 x_i + \delta_1 control_i + \varepsilon_i^y$$

(1b) $$m_i = \alpha_0 + \alpha_1 x_i + \delta_2 control_i + \varepsilon_i^m$$

In these models, the parameters (α, β, γ, δ) represent the effects of each of the variables on Y. The error terms ε_i^y and ε_i^m are assumed to be i.i.d. normal, $\varepsilon_i^y \sim N(0, \sigma_y^2)$ and $\varepsilon_i^m \sim N(0, \sigma_m^2)$, so that this model consists of two independent multiple regression equations. In our model, we note that due to the strategic behaviour in the use of language, the error terms are correlated and hence the parameter estimates would be biased because $E(m_i | \varepsilon_i^y) \neq 0$.

To deal with this endogeneity, we follow the approach described by Zhang, Wedel, and Pieters (2009) which is an extension of the LIV approach developed by Ebbes and colleagues (2005). Using this approach, we specify the model as follows:

(2a) $$y_i = \beta_0 + \beta_1 \tilde{m}_i + \beta_2 \tilde{m}_i z_i + \beta_3 \tilde{m}_i w_i + \beta_3 \tilde{m}_i w_i z_i + \gamma_1 x_i + \delta_1 control_i + \varepsilon_i^y$$

(2b) $$m_i = \tilde{m}_i + \varepsilon_i^m = \alpha_0 + \alpha_1 x_i + \theta_1 v_i + \delta_2 control_i + \varepsilon_i^m$$

where all variables are as defined previously. In mediation model (Equation 2b), the instrumented assessment predominant regulatory mode orientation language ($\tilde{m}_i$) is a function of who tweets (x_i) and an unobserved LIV, v_i. We assume that v_i follows a Bernoulli distribution, $v_i \sim B(\pi^v)$, where $\pi^v = P(v_i = 1)$ is the instrument probability. The parameter θ represents the effect of the latent instrument v_i on the APL. By construction, $\tilde{m}_i$ is uncorrelated with the error term in the main equation ε_i^y. We estimate the model with Markov chain Monte Carlo (MCMC) methods by recursively sampling from the full conditional distributions of the parameters of the models in question. An advantage of the MCMC estimation is that it allows for computation of the standard error of a mediated indirect effect in a straightforward manner. The posterior distributions are standard conjugate distributions. We assume normal $N(0, 10^4)$ prior distributions for all regression coefficients and inverse gamma $IG(10\sim3, 10\sim3)$ prior distributions for the variance parameters. We use a burn-in of 30,000 draws from the full conditional posterior distributions and 20,000 target draws. In Table WA1, below we report the three-way interaction and indirect effect as reported in Model 4 in Table 3 and then also the endogeneity corrected coefficients estimated using the procedure described above. We note that the direction of the effects does not change, however, the coefficients are much larger. We also note that the coefficient for the residual standard deviation of the LIV is not significant and hence conclude that the method has accounted for the endogeneity and is reporting the bias corrected coefficients.

	Model 4	Model 4 with LIV
Three-way interaction		
APL x Executive Power x Legislative Power	0.057*** (0.016)	182.9* (9.398)
Indirect Effects		
Who Tweets → APL → Retweet Count	0.013† (0.001)	351.3* (35.0)
Residual SD		-0.005 (004)

Table WA1. Comparing Parameter Estimates

Sample OpenBUGS program for Moderated – Mediation Analysis with One X-variable, control variables for year, Endogeneity of the Mediator and Two Moderator Variables

```
# Bayesian Mediated - Moderation model with endogeneity of the mediator
# Example program for one x-variable and one control variable
# Initial values for parameters and data should be read from separate files
# Here:
# N is total number of observations
# y[.] is dependent variable (Y)
# m[.] is the (endogenous) mediator (M)
# x[.,1] is the possibly mediated regressor (X)
# w[.,1] and z[.,1] are the moderators (W, Z)
# timefixed[.,1] is a control variable
# Output: alpha, beta, gamma, lambda, rho, p, zeta, sigma

model {
for (i in 1:N) {
        mu.y[i] <- beta[1] + beta[2]*mu.m[i] + gamma*gopY[i] + rho*(apl[i]-mu.m[i])  +
                        timefixed[i] + mode[i]
        # Time fixed effects for the main model
        timefixed[i] <- delta[1]*created08[i] + delta[2]*created09[i] + delta[3]*created10[i]
        # Moderated Mediation Effects
        mode[i] <- psi[1]*mu.m[i]*senateY[i] + psi[2]*ppY[i] + psi[3]*senateY[i]*ppY[i]
        # Mediation Model
        mu.m[i] <- alpha*gopY[i]+lambda[ V[i] ] + tf[i]
        # Time fixed effects for the main model
        tf[i] <- delta1[1]*created08[i] + delta1[2]*created09[i] + delta1[3]*created10[i]
        rtCnt[i] ~ dnorm(mu.y[i],xsi[1]) # Distribution of Y
        apl[i] ~ dnorm(mu.m[i],xsi[2]) # Distribution of M
        V[i] ~ dcat(p[]) # Latent discrete instruments

        dump[i] <- thorY[i] + congressY[i] # unused moderators

        }

        p[1] ~ dbeta(1,1) # Prior for the latent instrument probabilities
        p[2]<-1-p[1]

        lambda[1] ~ dnorm(0, 0.0001) # Distribution of the latent instrument coefficients
        lambda[2] <-lambda[1] + nu
        nu ~ dnorm(0, 0.0001)I(0,)

        for (q in 1:2) {
                beta[q] ~ dnorm(0.0, 0.0001) } # Priors for coefficients in the Y-regression
        alpha ~ dnorm(0.0, 0.0001) # Prior for the coefficient of X in the M-regression
        gamma ~ dnorm(0.0, 0.0001) # Priors for indirect effect of X in the Y-regression
        for(j in 1:3){ delta[j] ~ dnorm(0.0, 0.0001)} # Priors for the time fixed effects
        for(j in 1:3){ delta1[j] ~ dnorm(0.0, 0.0001)} # Priors for the time fixed effects in LIV
        for(k in 1:3) { psi[k] ~ dnorm(0.0, 0.0001)} # Priors for the moderated effects
```

```
rho ~ dnorm(0.0, 0.0001) # Prior for the residual Y-M covariance
for (q in 1:2) {
        xsi[q] ~ dgamma(0.001,0.001)} # Prior for precision of the errors in Y and M
for (q in 1:2) { sigma[q] <- sqrt(1/xsi[q])} # Residual SD Y and M

# Indirect effect of X on Y
zeta<- beta[2]*alpha + psi[1]*alpha + psi[2]*alpha + psi[3]*alpha

} # model statement ends
```

Speculative Discussion of Future Research Directions For Parties Without Executive Power
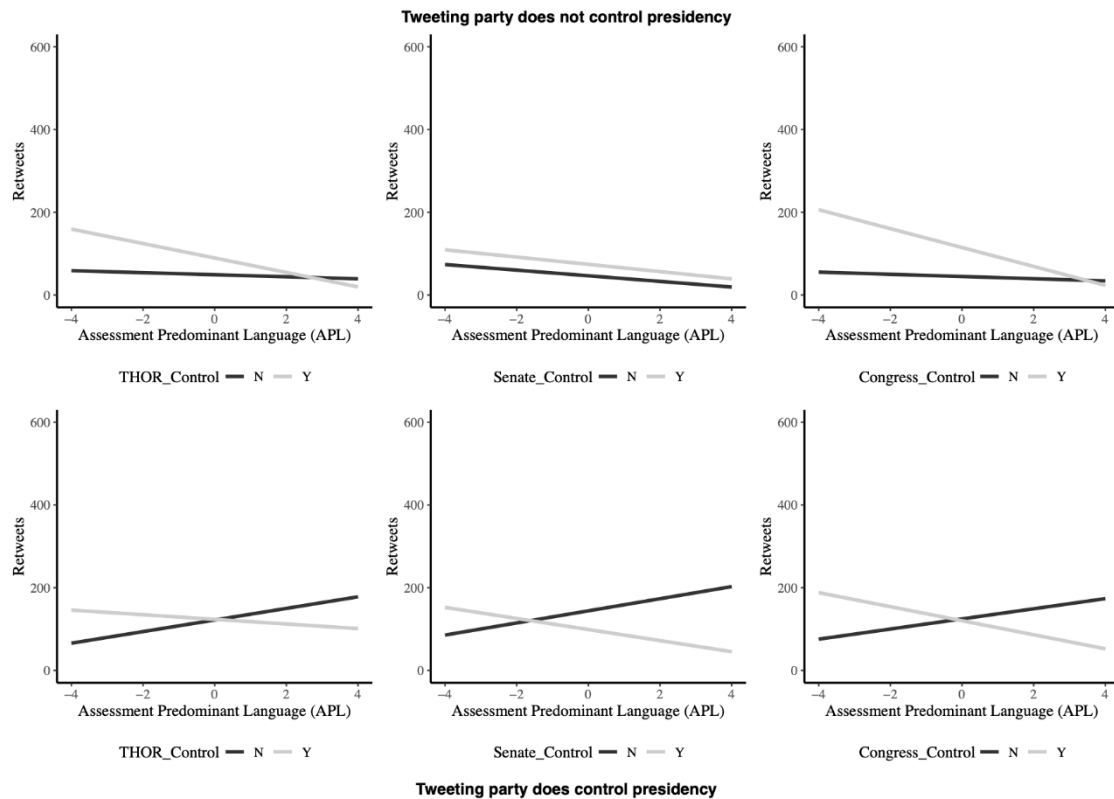

Figure 3. Effect of APL on Retweets Depending on Control of the Executive or Legislative Branches of Government

The above graphical representations depict how various combinations of executive and legislative power impact the effects of regulatory mode language on sharing. In the upper panel, it can be seen that parties without control of either the legislative or the executive branch of government receive very few retweets overall, with regulatory mode language also appearing to have little impact whatsoever on content virality. While this situation is beyond the intended scope of work presented in this paper, it may be because parties who do not have control of any branch of government will get less attention both on social and traditional media generally. Further, because parties without control of either branch of government have no power over the system of checks and balances, it is possible that regulatory mode language reflecting power over those checks and balances will be less likely to affect the virality of their content. The fact that there is no consistent pattern in the top three graphs is further in line with these ideas. Future research would therefore have to be conducted in order to understand what the key drivers of sharing are for content from parties without control of any branch of government, such as from third parties.

It can also be seen in the above graphs that assessment language does not increase virality from parties that only control the legislative branch of government. However, we refrain from providing argumentation as to why this is, as we believe that the power derived from controlling only the legislative differs from controlling the executive, and therefore that

material on this topic is separate to the scope of our paper. Firstly, given that those with only legislative control do not set the policy agenda (the executive does), their communication is unlikely to be as impacted by the power to advance their agenda as it would be with the executive. Secondly, the degree of power possessed by the legislative branch cannot be conceptualised as clearly as that of the executive. This is because the legislative branch can be considered to be high in power because it controls the passage of legislation (whereas the executive must work to have congress pass legislation on its behalf), but low in power because both the executive and the other house of congress can also act as a check on legislative power.

Given that our second hypothesis relates to how power in a system of checks and balances can impact the prosecution of a political agenda, the unclear nature of legislative power, and the inability of the legislative to set the political agenda would therefore likely impact regulatory mode language differently when compared to the executive. As such, we cannot provide explanations for how controlling only the legislative branch of government would affect sharing of regulatory mode language. Any exploration of this topic must therefore be left up to future research on the subject.

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