



Brief Textual Indicators of Political Orientation

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Abstract

Language reflects one's thoughts, feelings, and worldview. Technology has led to a proliferation of brief communications. Is this brief text meaningful? We examine whether text from brief political and nonpolitical communications reflect political ideology. Student responses to their ideological foundations (Study 1), brief snippets of unanimous Supreme Court verdicts (Study 2), and celebrity tweets (Study 3) were textually analyzed to examine whether they contained perceived threat and resistance to change content and whether this predicted the authors' political affiliation. Across three studies, words related to resistance to change, but not perceived threat, were related to political ideology such that conservatives were more likely to include resistance-to-change-related words in their responses compared with liberals. These results suggest that brief text, even when not overtly political, reflects one's political ideology. The increase in brief text production via new technology and its ability to predict political ideology make these findings particularly meaningful.

Keywords

political orientation, computer-mediated communication, affiliation, Twitter, brief text communication

Modern technology has ushered in an era of brief communication not seen since the proliferation of the telegraph (Hochfelder, 2012). For instance, a 2007 study found that American participants' average text messages were 7.7 words in length (about 35 characters), and their average instant message was 6.0 words in length (about 29 characters; Ling & Baron, 2007). Twitter posts, with a maximum length of 140 characters, typically contain a whopping 30 characters (Panzarino, 2012). The following set of

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studies show that brief messages can indicate complex, pervasive characteristics of the speakers, such as their political orientation. Specifically, consistent differences should be observed in language use among liberals and conservatives, and not just when they are talking politics.

Political Orientation as a Pervasive Worldview

Political orientation has been seen as a concise proxy for one's broader worldview. This extends to foundational psychological constructs. For instance, Haidt (2012) determined that political beliefs are largely shaped by broader senses of right and wrong. Westen (2007) described how political affiliation has less to do with rational analysis of the consequences of specific positions and more to do with broader emotional reactions. As a consequence, liberals and conservatives are consistently on the opposite side of a wide range of issues, and the polarization in the United States has only increased in recent years (Pew Research Center, 2017a). For example, liberals and conservatives in the United States remain at opposite ends of the continuum on issues such as acceptance of homosexuality (54% of Republicans support, compared with 83% of Democrats), the view that immigration strengthens the country (42% of conservative Republicans, compared with 84% of liberal Democrats), and supporting gun rights (79% of Republicans, compared with 20% of Democrats; Pew Research Center, 2017b).

In their often-cited meta-analysis, Jost, Glaser, Kruglanski, and Sulloway (2003) established several variables that predict political conservatism: intolerance of ambiguity, integrative complexity, openness to experience, uncertainty tolerance, self-esteem, fear of loss, mortality salience, system instability, and one's need for order, structure, and closure. The authors recognized the heavy conceptual overlap between many of these constructs and consolidated them into two primary motivational differences between liberals and conservatives: compared with liberals, conservatives are more sensitive to threat and more resistant to change.

Individuals high in threat sensitivity and resistant to change typically find greater comfort in conservative ideologies compared with liberal ideologies (Jost et al., 2003). Neuroimaging research indicating greater amygdala activation (associated with affective aspects of decision making) and decreased activation of the insular cortex (associated with greater self-awareness of one's physiological reactions to affective experience) among conservatives compared with liberals (Schreiber et al., 2013) implies an increased tendency to experience a reflexive emotional reaction and a decreased tendency to recognize that its origin contributes to threat sensitivity. Threat, in turn, is likely to produce negative emotion (e.g., Zhang, Liu, Wang, Ai, & Luo, 2016). In fact, conservatism has been linked to negative emotion in several studies dating back decades (Adorno, Frenkel-Brunswick, Levinson, & Sanford, 1950; Altemeyer, 1996, 1998; Duckitt, 2001; Krugman, 2002; Stone, 1989; Tomkins, 1963, 1965). For example, the world is perceived as more threatening to conservatives (Altemeyer, 1998; Duckitt, 2001), conservatives are more likely to run negative political ads (Lau & Rovner, 2009) and have increased disgust sensitivity (Inbar, Pizarro, & Bloom, 2008).

This threat sensitivity component further explains conservatives' characteristic discomfort with change, in that, encountering new and legitimate perspectives can undercut one's perceptions of certainty and stability, which has the potential to produce anxiety (Rokeach, 1960). Thus, individuals who are especially sensitive to threat would be highly motivated to maintain certainty and perceived stability in their environment and worldview. Conservative ideology provides an antidote to this uncertainty (and, by extension, to threat and negative emotion) by emphasizing structure, hierarchy, and tradition, and resistance to social change (Conover & Feldman, 1981).

Language Can Reflect and Shape Our Worldview

Language has long been thought to reflect one's worldview (Tohidian, 2009). Whorf (1956) viewed language as a means of molding and programming our thoughts. Piaget (1959) viewed that same relationship as working in the opposite direction: He emphasized how our thoughts are reflected in our language choices. Many studies (e.g., Macgillivray, 2008; Niewiara, 2010), in turn, have established how one's lexical choices can illustrate the personal and ideological values of the speaker.

In fact, many of the specific ideological and behavioral manifestations of what it means to be a conservative or liberal can be traced back to the fundamental ways of interpreting and responding to the world around us, which are reflected in our word choices. This has been shown in studies that code verbal output for thematic content (e.g., using presidential advertisements, Moses and Gonzales, 2015, found greater prevalence of a "strict father" theme from Republican candidates and a greater prevalence of a "nurturant parent" theme from Democratic candidates), as well as in studies that analyze the specific text that comprises a message. For example, studies have shown that liberals are more likely to use depressive language (Slatcher, Chung, Pennebaker, & Stone, 2007), more positive-emotion-related language (e.g., Wojcik, Hovasapian, Graham, Motyl, & Ditto, 2015), and more future-oriented language than conservatives, while conservatives are more likely to use past-oriented language (Robinson, Cassidy, Boyd, & Fetterman, 2015) and nouns than liberals (Cichocka, Bilewicz, Jost, Marrouch, & Witkowska, 2016). A study by Robinson, Boyd, and Fetterman (2014) showed characteristic differences between liberals and conservatives in the use of words, indicating approach versus avoidance emotions, even when participants were writing on nonpolitical topics.

To derive these results, many of these studies analyzed massive amounts of text. For example, Slatcher et al. (2007) used transcripts from 271 interviews, press conferences, and debates provided by political candidates. The aforementioned study by Robinson et al. (2015) used text from 145 State of the Union Addresses. This raises the question of whether copious amounts of text are necessary to detect motivational and ideological differences between communicators.

Communicating in a Postcard Society

Media communications have shrunk. Newspaper articles have become shorter in recent years (Farhi, 2014). Television news has relied on sound bites for decades (e.g.,

Hammond, Roberts, & Sulfaro, 2016), but even the sound bites, are becoming more bite sized (Fehrman, 2011). Recent technology changes have made the shortening of interpersonal communications even more pronounced.

New technologies such as Twitter, Facebook, and text messaging have increased the extent to which individuals communicate electronically with one another (Okdie et al., 2014). Increases in electronic communication have put an enormous amount of accessible behavioral information into the public sphere, and research indicates that usage and access to longer online communications, such as blogs, are related to individual differences in characteristics, such as gender and personality (cf. Guadagno, Okdie, & Eno, 2008). However, much of the modern textual communication channels, by design or by necessity, limit the length of transmissions (e.g., Twitter limits messages to 140 characters). Shorter messages are typically associated with less depth (Shaw, 2013) and complexity (Chavez, Montano, & Barrera, 2016) in communication. Brief text messages are no exception; a recent study (Lyddy, Farina, Hanney, Farrell, & O'Neill, 2014) analyzed 936 text messages and reported that 46% of the content was accounted for by the 100 most frequently used words. Little research has investigated the extent to which the text produced from brief messages is associated with many of the individual differences factors (e.g., political orientation) that longer messages can predict.

A conceptual parallel may be found in the literature on “thin slices” of behavior. This line of research shows that a few seconds of expressive behaviors can contain an enormous wealth of individuating information to which observers detect and readily respond (Ambady, Bernieri, & Richeson, 2000). Although brief video clips may fail to provide adequate information to make accurate assessments of some traits that can only be determined over a longer term (e.g., task-oriented traits like persistence), they typically provide enough information to form quite accurate judgments of interpersonal functioning (e.g., interpersonal warmth; Ambady, Krabbenhoft, & Hogan, 2006). Similarly, it seems possible that small sections of text can provide evidence of certain essential motivational elements of one's worldview, even if this amount is insufficient to assess perspectives that are more complex or less accessible.

The goal of the current set of studies is to examine whether brief text communications (e.g., Twitter) are predictive of individual differences (e.g., political ideology). Conservative ideology is closely linked to threat sensitivity and resistance to change (e.g., Jost et al., 2003). So we specifically predict that text from conservatives will contain more words indicating fear or anger (e.g., “hate” or “worried”) compared with liberals. This is because high-arousal negative emotion is a reflexive response to perceived threat (e.g., Zhang et al., 2016). We also anticipate that text from conservatives will contain more words indicating inhibition (e.g., “stop”) compared with liberals. This is because inhibition overlaps with the concept of resistance to change.

The following studies featured diverse samples of participants and examined language differences between liberal and conservatives using much smaller language samples than are typically analyzed in this type of research. While there is no universal definition as to what constitutes a “brief text communication,” for this article, the

longest block of text we analyzed was 300 words. Our goal was to show that text blocks of this length, as well as smaller text blocks, could be meaningfully analyzed. This includes blocks of text smaller than the 50-word minimum that many text analysis programs recommend—including the text analysis program used in each of the studies in this manuscript. For the purposes of replication and the generalization of our effect, we deliberately used a broad range of textual sources and varied our methods between studies. The current studies are some of the first that investigate whether brief text that is not overtly political is reflective of one's political ideology. Study 1 analyzed undergraduates' brief explanations for why they affiliate with a political party. We used this study to determine whether the expected linguistic indicators of motivation would be present in overtly political statements. Study 2 analyzed opening passages of Supreme Court opinions using longer selections of text and a much more nuanced measure of political ideology. Study 3 used Twitter posts from celebrities who endorsed a particular presidential candidate. Neither set of text used in the latter two studies was overtly political, but we expected the same pattern of linguistic indicators of motivation to emerge that we found in Study 1.

Hypotheses

Hypothesis 1: Conservatives will mention categories associated with threat (i.e., negative emotion) more than liberals in brief text communication.

Hypothesis 2: Conservatives will mention categories associated with resistance to change (i.e., inhibition) more than liberals in brief text communication.

Study 1

Method

Participants. A total of 345 undergraduate psychology students (173 female; $M_{\text{age}} = 18.59$, $SD = 1.34$) from a state university in Ohio participated in this study in exchange for extra credit. Participants self-reported ethnicity, and 67% of participants identified as Caucasian, 17% as African American, 4% as Asian or Asian American, 1% as Latino or Hispanic, 10% as other, and 1% did not specify.

Procedures. As part of a larger study, participants completed the required measures in a cubicle on a computer. The central questions to which they responded were "What political party, if any, do you most closely associate with?" and "Why do you identify with your chosen political party?" The latter question was more germane for the current study, and any responses beyond "none" or "not applicable" were included in the analysis. Responses were brief, averaging 16.92 ($SD = 14.61$) words, slightly longer than the average Twitter post (Panzarino, 2012). Responses were analyzed for 141 participants identifying as "Democrat" or "Liberal," 118 participants identifying as "Republican" or "Conservative," 75 participants identifying as "Independent" or "Unaffiliated," and 11 participants identifying as "Libertarian."

Participants also indicated their Political Orientation (i.e., the degree to which they were liberal or conservative) on a Likert-type scale ranging from 0 = *Conservative* to 6 = *Liberal*. This interval variable served as the main predictor variable of interest. Although more nuanced measures for political orientation do exist, using a single-item measure is rather common (e.g., Grina, Bergh, Akrami, & Sidanius, 2016; Mostafa, 2016; Tullett, Hart, Feinberg, Fetterman, & Gotlieb, 2016).

Linguistic Inquiry and Word Count Analysis. A text analysis program called the Linguistic Inquiry and Word Count (LIWC; Pennebaker, Chung, Ireland, Gonzales, & Booth, 2007) was used to analyze participants' responses to the open-ended question "Why do you affiliate with your chosen political party?" LIWC processes text files and groups the various words into categories, such as personal pronouns, happiness-related words, sadness-related words, and so forth. It then provides output in the form of the percentage of the total word count for which those categories account.

Many LIWC categories have been correlated with psychometric characteristics. For example, the use of personal pronouns can indicate the direction of one's social focus, such that using first-person singular pronouns would indicate a focus on the self, whereas using third-person singular pronouns would indicate a focus on others (Tausczik & Pennebaker, 2010). We identified word categories involving specific psychometric characteristics (based on meta-analytic data; Tausczik & Pennebaker, 2010) that could be readily associated with either perceived threat or resistance to change. Thus, we did not analyze all 90 possible categories of words but instead analyzed only two sets of variables that we deemed especially pertinent.

The experience of threat involves the perception of *potential* loss (e.g., of stability, status, and self-esteem; Jost et al., 2003). The threat of loss often triggers negative, high-arousal emotions, such as anger and fear (Danesh, 1977; Zhang et al., 2016). The most directly applicable category provided by LIWC involves words associated with negative emotion—especially anxiety-related (e.g., worried, fearful, nervous) and anger-related (e.g., hate, kill, annoyed) words.

The concept of resistance to change involves a focus on tradition and maintaining the status quo (Jost et al., 2003). The most directly applicable category provided by LIWC involves inhibition-related words (e.g., block, constrain, stop).

Covariates. In addition to the fact that conservatives in the United States tend to be older and disproportionately male, as compared with liberals (Pew Research Center, 2016), previous studies have shown that individual demographic characteristics can influence language use. For example, studies have identified age as a significant predictor of linguistic tendencies (e.g., people show less self-focus as they age; Pennebaker & Stone, 2003), while others have identified gender differences (e.g., females use more social words; Newman, Groom, Handelman, & Pennebaker, 2008). To account for the influence of these factors, both age and gender were included as covariates.

We also included total Word Count for each statement as a control variable. This is because participants' statements were not a standardized length, and the more words one provides, the more likely one is to feature a LIWC category.

Table 1. Correlations Between Variables in Study 1.

Variable	1	2	3	4	5	6	7	8	
1. Political Orientation	1.00								
2. Participant Age	-.10 [†]	1.00							
3. Participant Gender	.03	-.14**	1.00						
4. Word Count	-.01	-.01	-.03	1.00					
5. Negative Emotion	.07	.19**	.03	.11*	1.00				
6. Anxiety	—	—	—	—	—	1.00			
7. Anger	.02	.05	.05	.03	.73**	—	1.00		
8. Sadness	.08	.35**	-.01	.02	.45**	—	.03	1.00	
9. Inhibition	-.19**	.08	-.03	.06	-.04	—	.00	-.03	1.00

[†] $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Results

Threat. To examine whether political orientation predicts the use of threat words, we conducted a series of standard linear regressions with Political Orientation as the main predictor and Participant Age, Participant Gender, and Word Count as covariates. See Table 1 for correlations among all the variables. The first outcome variable analyzed was Negative Emotion. The overall regression was significant, $p < .001$. See Table 2 for results of the regression. Political Orientation was a nonsignificant predictor ($p = .091$) of negative emotion-related words. Participant Age was a significant predictor, $p < .001$, such that older participants showed more negative emotion. Word Count was a significant predictor, $p = .035$, such that the higher word counts were associated with a greater use of negative emotion-related words. Participant Gender failed to predict negative emotion, $p = .302$.

Because the results ran counter to what was expected, we further parsed the negative-emotion measure into anxiety-related, anger-related, and sadness-related words (see Table 2). No anxiety-related words were detected by the LIWC, so anxiety could not be analyzed. The overall regression for anger-related words was not significant ($p = .591$), and neither were Political Orientation ($p = .693$), Participant Age ($p = .259$), Participant Gender ($p = .324$), or Word Count ($p = .565$).

The overall regression for sadness-related words was significant, $p < .001$. Political Orientation significantly predicted sadness-related words, $p = .021$, such that conservatives were less likely to include sadness-related words in their responses than liberals. In addition, Participant Age was a significant predictor, $p < .001$, such that older participants included sadness-related words more than younger participants. Participant Gender failed to significantly predict the use of sadness-related words, $p = .453$, as did Word Count, $p = .589$.

Resistance to Change. The overall regression for inhibition-related words was significant, $p = .008$ (see Table 2). Political Orientation significantly predicted Inhibition, $p = .001$, such that conservatives were more likely to include inhibition-related words

Table 2. Regression Statistics for Study 1.

Overall regression	Predictors	<i>t</i>	β	<i>p</i>
Negative emotion, $F(4, 340) = 5.36^{***}$				
	Political Orientation	1.69	.09	.091
	Participant Age	3.89	.21	<.001
	Participant Gender	1.09	.06	.278
	Word Count	2.12	.11	.035
Anger, $F(4, 340) = 0.59$				
	Political Orientation	0.40	.02	.693
	Participant Age	1.13	.06	.259
	Participant Gender	0.99	.05	.324
	Word Count	0.58	.03	.565
Sadness, $F(4, 340) = 13.84^{***}$				
	Political Orientation	2.32	.12	.021
	Participant Age	7.24	.37	<.001
	Participant Gender	0.77	.04	.444
	Word Count	0.54	.03	.589
Inhibition, $F(4, 340) = 3.49^*$				
	Political Orientation	-3.41	-.18	.001
	Participant Age	1.09	.06	.275
	Participant Gender	-0.31	-.02	.757
	Word Count	0.09	.01	.925

* $p < .05$. ** $p < .01$. *** $p < .001$.

in their responses compared with liberals. Participant Age ($p = .275$), Participant Gender ($p = .757$), and Word Count ($p = .925$) failed to reach significance.

Alternate Analysis. Because the LIWC produces percentages of the total word count that various categories account for, there is the potential for dramatically skewed results with small samples of text (e.g., the presence of a category in a very short sentence would create a very high value). To account for this, we reran the analyses described above, except that we used binary logistic regressions to detect the presence or absence of the Negative Emotion and Inhibition categories. The results mirrored the original analyses (see Table 3).

Negative Emotion was detected in a total of 36 responses. When included in a logistic regression with Participant Age, Participant Gender, and Word Count, Political Orientation was a significant predictor of Negative Emotion, $p = .026$, such that conservatives used less negative emotion-related words than liberals. Age was a significant predictor, $p = .001$, such that older participants used more negative emotion-related words. Word Count was also a significant predictor, $p < .001$, such that a higher Word Count was associated with greater use of negative emotion-related words. Participant Gender was not a significant predictor ($p = .828$).

Table 3. Alternative Analysis for Study 1.

Overall Regression	Predictors	<i>B</i>	<i>SE B</i>	<i>Wald</i>	<i>e^B</i>
Negative Emotion, $\chi^2 = 51.88$, <i>df</i> = 4					
	Political Orientation	.28	.13	4.96*	1.32
	Participant Age	.35	.11	11.10*	1.42
	Participant Gender	.09	.41	0.05	1.09
	Word Count	.07	.01	34.34**	1.07
Inhibition, $\chi^2 = 53.52$, <i>df</i> = 4					
	Political Orientation	-.41	.11	14.10**	0.67
	Participant Age	.12	.10	1.39	1.13
	Participant Gender	.17	.35	0.24	1.19
	Word Count	.06	.01	28.75**	1.07

p* < .05. *p* < .01. ****p* < .001.

Inhibition was detected in a total of 50 responses. When included in a logistic regression with Participant Age, Participant Gender, and Word Count, Political Orientation significantly predicted Inhibition, $p < .001$, such that conservatives used more inhibition-related words than liberals. Word Count was also a significant predictor, $p < .001$, such that a higher Word Count was associated with greater use of inhibition-related words. Participant Age ($p = .238$) and Participant Gender ($p = .623$) were not significant predictors.

Discussion

The results from Study 1 supported Hypothesis 2: conservatives used more words indicating resistance to change (i.e., inhibition-related words) than liberals. However, the results did not support Hypothesis 1, as conservatives did not use more words indicating threat (e.g., negative emotion) compared with liberals. The only significant result was that liberals used more sadness-related words than conservatives. Although consistent with the results of Slatcher et al. (2007), this result was largely independent of the theoretical model, because sadness is not one of the negative emotions commonly viewed as a consequence of threat (e.g., Zhang et al., 2016).

Although it produced authentic responses with minimal prompting, this study featured three clear limitations. First, respondents were approximately 19 years old; many may not have particularly strong political opinions, and some of those with strong opinions may not be able to fully articulate those opinions. Second, responses were not standardized, so while one respondent might reply with an eloquent response of a few dozen words, another might respond in a four-word sentence fragment. In such a case, the former respondent potentially could score higher in nearly every LIWC variable. Finally, the average length of the text sections analyzed was less than ideal for a LIWC analysis. The LIWC website states, "The more words you analyze, the more trustworthy are the results. A text of 10,000 words yields far more reliable results than one of

100 words. Any text with fewer than 50 words should be looked at with a certain degree of skepticism” (Pennebaker Conglomerates, 2016). We wholeheartedly agree, and it is with this skepticism that we conducted Study 2.

Study 2 set out to replicate the results of Study 1 using alternatively sourced text that allowed us to bypass the limitations in Study 1. In Study 2, we analyzed brief snippets of unanimous U.S. Supreme Court decisions authored by various justices. Using this method standardized the length of the communication and ensured the presence of well-formed statements that were not overly political. Additionally, we substituted a more nuanced measure of political ideology for our single-item measure.

Study 2

Method

Selection of Text. To obtain blocks of text to analyze using LIWC, we first sought unanimous decisions authored by Supreme Court justices (see supplemental materials: osf.io/mgytk). Many of the decisions initially were identified using the Oyez Project website (<http://today.oyez.org/>) and similar sources. The unanimity of the decisions is important because, while concurrences are capable of being contentious, unanimous decisions are thought to be, by definition, less ideological than nonunanimous decisions. Prior to 1941, unanimous decisions on the Court were much more common (which changed when Justice Harlan Stone ascended to the position of Chief Justice and brought with him greater tolerance of descent; Sunstein, 2015), meaning that the fact that a vote was unanimous did not necessarily mean that the decision was not contentious or its wording not ideological. For this reason (and because they were easier to obtain), we focused on decisions authored after 1940.

We chose to analyze decisions from later, rather than earlier, in the justices’ careers as that allowed us to limit the age differences and cohort differences between the justices. Clearly, this applies less to the current Court (because several of them have not authored late-term decisions), but for the vast majority of decisions analyzed, this limited temporal differences. Using decisions that were among the last of the justices’ careers also allowed us to fit more justices into the 1941-to-present window.

Whenever possible, we attempted to analyze the first 300 words of each decision. One of the most problematic issues in analyzing these passages involved the inclusion of quotes. Supreme Court decisions frequently quote statutes and evidence presented by the trial court. On one hand, use of quotes involves a conscious decision by the author to include specific sections of recycled text, just like any other linguistic decision. On the other hand, we did not wish to analyze one judge’s use of another person’s writing. As a compromise, we limited the use of quoted text to 30 words (10% of the total) unless the use of quotation marks seemed arbitrary (e.g., one decision involving a labor dispute quoted the term *sit in* every time it appeared in the document, even though there are not many other concise ways to describe the concept).

In our effort to limit the “legalese” associated with judicial decisions, we focused on analyzing 300-word sections taken from the factual background of the cases,

starting from the beginning of the factual section. We omitted references, and if the factual background section was too short, or included long sections of block quotes, we discarded that case and selected another late-term case from the same justice. This method allowed us to obtain unanimous post-1940 decisions from 40 of the 41 justices serving on the Supreme Court during this period, with the lone exception being Justice Owen J. Roberts, who served on the Court until 1945 (Oyez Project, 2016).

Once the text was identified, we submitted it for analysis using the LIWC. Three hundred words is a somewhat arbitrary limit, but we adhered to that in order to provide standardized input that was within the recommended length for LIWC analyses. Also, because we were dealing with a smaller sample size, we wanted a more substantial section of text to analyze. Selection of the specific Supreme Court decisions was partly influenced by convenience (in both obtaining and analyzing the decisions), rather than exclusively involving the absolute last unanimous case a specific justice authored. However, the arbitrary aspects of the selection criteria are not a weakness; we merely sought to show that, using nonideological writings from a distinct population, we could replicate the results from Study 1. So, while Study 1 featured overtly political statements by undergraduates of a nonstandard length, Study 2 featured minimally political statements by Supreme Court justices of a standard length.

Quantifying Ideology. In Study 2, we utilized a more nuanced and objective measure of political ideology than the single-item, self-report measure used in Study 1. Epstein, Landes, and Posner (2015) created a voting index of the individual justices on the Supreme Court, going back to 1938. They used the fraction of conservative votes on nonunanimous cases for each justice and used the votes of “moderate” justices to adjust for the influence of nonideological factors. With scores ranging from .166 (least conservative) to 1.00 (most conservative), this measure showed a strong positive correlation with those judges’ tendency to cast conservative votes in 5–4 decisions ($r = .98, p < .01$, for the current sample; data provided by Epstein et al., 2015).

Covariates. As with Study 1, we included the gender of the individual justices as a covariate. To account for cohort differences, we included the birth year of the justices as a second covariate. Word Count was standardized, so this was not included as a covariate.

Results

Threat. To examine whether political ideology predicts the use of threat words, a series of standard linear regressions were conducted using Ideology as the main predictor and Birth Year and Gender as covariates. See Table 4 for correlations between all variables. The first outcome variable analyzed was Negative Emotion. The overall regression was significant, $p = .021$. See Table 5 for regression results. Ideology failed to significantly predict Negative Emotion ($p = .393$). Birth Year was a significant predictor, $p = .004$, such that justices born later used more negative emotion-related words. Gender failed to significantly predict Negative Emotion, $p = .106$.

Table 4. Correlations Between Variables in Study 2.

	1	2	3	4	5	6	7
1. Ideology	1.00						
2. Birth Year	-.05	1.00					
3. Gender	-.23	.46**	1.00				
4. Negative Emotion	.17	.37*	-.08	1.00			
5. Anxiety	-.04	.31†	.50**	.11	1.00		
6. Anger	.14	.29†	-.19	.85**	-.06	1.00	
7. Inhibition	.28†	.00	.10	-.19	.08	-.05	1.00

† $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

The overall regression for Anxiety was significant, $p = .011$. Ideology failed to significantly predict Anxiety ($p = .644$). Gender was a significant predictor, $p < .007$, such that female justices used more anxiety-related words than male justices. Birth Year failed to significantly predict Anxiety, $p = .570$.

The overall regression for Anger was significant, $p = .024$. Ideology failed to significantly predict Anger ($p = .626$). Gender was a significant predictor, $p = .025$, such that female justices used fewer anger-related words than male justices. Birth Year was also a significant predictor, $p = .006$, such that justices born later used more anger-related words.

Resistance to Change. The overall regression for inhibition-related words was not significant, $p = .212$ (see Table 5). However, Ideology was a significant predictor such that conservative justices used inhibition-related words more than liberal justices, $p = .049$. Birth Year ($p = .629$) and Gender ($p = .235$) failed to significantly predict the use of inhibition-related words.

Discussion

The results of Study 2 were nearly identical to Study 1, in that the use of inhibition-related words stood out as the lone, significant linguistic difference predicted by political ideology, and the effect was in the same direction. This effect persisted, despite the marked changes in methodology between the two studies, the smaller sample size, and the less overtly political text samples. In Study 3, we sought to determine whether this result would persist using smaller sections of text (as with Study 1) from sources that were not overtly political (as with Study 2). We did so using celebrity Twitter posts (tweets).

Study 3

Method

Selection of Text. First, we used Internet searches to identify celebrities who had endorsed a particular political candidate for president early on in the primary season.

Table 5. Regression Statistics for Study 2.

Overall regression	Predictors	<i>t</i>	β	<i>p</i>
Negative Emotion, $F(3, 36) = 3.66^*$				
	Ideology	0.86	.13	.393
	Birth Year	3.09	.51	.004
	Gender	-1.66	-.28	.110
Anxiety, $F(3, 36) = 4.29^*$				
	Ideology	0.47	.07	.644
	Birth Year	0.57	.09	.570
	Gender	2.87	.48	.007
Anger, $F(3, 36) = 3.54^*$				
	Ideology	0.49	.07	.626
	Birth Year	2.90	.48	.006
	Gender	-2.34	-.40	.025
Inhibition, $F(3, 36) = 1.58$				
	Ideology	2.04	.33	.049
	Birth Year	-0.49	-.09	.630
	Gender	1.21	.22	.235

* $p < .05$. ** $p < .01$. *** $p < .001$.

Beginning our search in this manner ensured that the chosen celebrities' political affiliation was done by a third party and was publicly verifiable (see supplemental materials for the celebrities and the published source of the endorsements). We avoided endorsers who were famous exclusively for their political activities. This allowed us to retain Arnold Schwarzenegger, Jesse Ventura, and Sarah Palin, while dropping former New Hampshire governor John Sununu and Maine governor Paul LePage. Second, we divided the endorsers into four groups: those who endorsed Hillary Clinton, those who endorsed Bernie Sanders, those who endorsed Donald Trump, and those who endorsed Republican candidates who were not Donald Trump (the original design involved a fourth category composed of Jeb Bush endorsers, but Jeb Bush had no celebrity endorsers, and no single non-Trump candidate had more than eight endorsers). Celebrities were only removed from consideration if they (1) later claimed to have made the endorsement in jest, (2) two different websites conflicted as to which candidate a specific celebrity endorsed, and (3) were only celebrities in a political capacity. Next, we attempted to find 15 to 20 endorsers from each group who maintained Twitter accounts and recorded the first 10 Tweets, starting on January 25, 2016, for each endorser. We ultimately found 17 Clinton endorsers, 19 Sanders endorsers, 16 Trump endorsers, and 18 endorsers of other Republicans who met these criteria.

We then collapsed the Clinton and Sanders endorsers together (producing 36 Democrat endorsers) and the Trump and Republican endorsers together (producing 34 Republican endorsers). A birth year for each of the endorsers was obtained using the International Movie Database (www.imdb.com). The Republican endorsers were older ($M_{\text{birth date}} = 1961$) than the Democrat endorsers ($M_{\text{birth date}} = 1972$), and most were male

Table 6. Correlations between Variables in Study 3.

	1	2	3	4	5	6	7
1. Political Party	1.00						
2. Birth Year	-.38**	1.00					
3. Gender	.32**	-.29*	1.00				
4. Negative Emotion	-.11	-.13	.01	1.00			
5. Anxiety	-.09	.04	.06	.32**	1.00		
6. Anger	-.11	-.16	-.01	.71**	.02	1.00	
7. Inhibition	.27*	-.18	-.03	-.09	-.11	.07	1.00

* $p < .05$. ** $p < .01$. *** $p < .001$.

(82%, compared with 53% for Democrat endorsers). On average, Republican endorsers required 14.47 days ($SD = 14.90$) to reach 10 Tweets, compared with 13.08 days ($SD = 9.46$) for Democrats, but this difference was not statistically significant, $p = .646$.

Finally, we submitted all the Tweets to an LIWC analysis. The sections of text analyzed averaged 129.91 words (i.e., about 13 words per Tweet). Sections of analyzed text from Republican endorsers ($M = 134.41$, $SD = 27.22$) were slightly longer than from Democrat endorsers ($M = 125.67$, $SD = 33.60$), but this difference did not reach significance, $p = .237$. For this reason, and because Word Count was not a particularly reliable or powerful predictor in Study 1, we did not include it as a covariate in this study.

Results

Threat. Our statistical analyses consisted of a series of analyses of variance (ANOVAs) using one two-level independent variable: the political party of the candidate that the individual celebrity endorsed ("Party"). We conducted ANOVAs rather than t tests to control for Birth Year and Gender of the endorser. See Table 6 for correlations between all variables.

No significant difference emerged between parties for use of negative emotion-related words ($p = .156$). Neither Birth Year ($p = .149$) nor Gender ($p = .892$) achieved significance.

There was no significant difference between parties for use of anxiety-related words ($p = .395$). Birth Year ($p = .823$) and Gender ($p = .412$) also failed to reach significance.

There was no significant difference between parties for use of anger-related words ($p = .147$). However, Birth Year ($p = .823$) was marginally significant, $F(1, 66) = 3.38$, $p = .071$, $\eta = .22$, such that the later an endorser was born, the less likely he or she was to use anger-related words. Gender did not predict anger-related words, $p = .895$.

Resistance to Change. Party significantly predicted the use of inhibition-related words, $F(1, 66) = 4.14$, $p = .046$, $\eta = .22$, such that Republicans were more likely to use inhibition-related words ($M = 0.54$, $SD = 0.65$), compared with Democrats ($M = 0.24$, $SD = 0.44$). Birth Year ($p = .343$) and Gender ($p = .251$) were not significant.

Discussion

The results for Study 3 were nearly identical to Studies 1 and 2. Once again, use of inhibition-related words stood out as the only significant linguistic difference between liberals and conservatives, and in the predicted direction. Political party was able to predict the use of inhibition-related words, even when both gender and birth year were controlled for. Thus, we were able to replicate the results of the previous studies using yet another distinct sample and relatively small sections of text that were not overtly political, thereby increasing the generalizability of our effect.

General Discussion

Across three studies utilizing text produced in unique ways, use of inhibition-related words reliably differed based on political ideology, suggesting a replicable robust effect. In Study 1, we analyzed 17-word statements from college freshmen that were explicitly about political affiliation. Study 2 featured an analysis of 300-word, unanimous legal decisions from Supreme Court justices about assorted minimally ideological topics. Study 3 extended these findings with an analysis of random Twitter postings by celebrities. All three studies featured remarkably similar results despite the extreme differences in populations, writing motivations, content, and context. The explicitly political text analyzed in Study 1 allowed us to establish the presence of this expected linguistic indicator of motivations underlying political ideology, which was then replicated in Studies 2 and 3 using effectively nonpolitical statements. This implies that some indicators of one's worldview that forms one's political ideology are present in brief language samples, even when outside the context of that ideology. This also poses the tentative possibility that the LIWC analysis may be more sensitive to small sections of text than even its creators anticipated.

Threat perception, as measured in the current study, was mainly an affective construct, and we can speculate that it may have been less overtly accessible by participants. For instance, in the 345 statements analyzed in Study 1, not a single one yielded an anxiety-related word. So while we know from meta-analyses (e.g., Jost et al., 2003) that conservative ideology is motivated by perceived threat and resistance to change, of the categories measured in this study, only the category most closely linked with resistance to change showed a significant relationship.

It also is possible that because participants adopted an insular worldview, they were saved from the prospect of threat. That is, if resistance to change is a rational response to perceived threat, then it may serve to reduce the degree to which one perceives threat. Although intuitively attractive, the current study does not test that hypothesis, and as such, it is speculation.

Alternately, the lack of significant differences between liberals and conservatives in terms of the negative emotion words used may have been methodological. After all, our results regarding negative emotion contradict those of previous studies (Robinson et al., 2014; Wojcik et al., 2015) that analyzed much larger sections of text. A study by Tov, Ng, Lin, and Qiu (2013) showed that detecting negative emotion using the LIWC is inconsistent and a function of situational factors, such as immediacy of the event

and whether one is identifying an acute state rather than a general mood. So while it is possible that these affective differences existed among the diverse samples used in the current studies, and these emotions may have been *eventually* accessible, perhaps they were less *immediately* accessible compared with inhibitory motivations. Although speculative, this makes some degree of intuitive sense; if someone takes a defensive action and is asked why, that person is likely looking to express the desire to stop the source of the threat before getting around to adding “because I was afraid.” In Study 1, for example, a longer explanation might have included both the surface and the underlying motivations, while a shorter explanation might not. In sum, noninhibitory motivations (e.g., threat) are likely present in long-form text but are less likely to be revealed in brief snippets of text.

Limitations and Future Directions

We attempted to avoid validity issues by using a variety of textual sources, but textual analysis almost inherently involves some degree of subjectivity on the part of the researchers (e.g., in selecting what and how much of something to analyze). Future researchers could replicate the current work analyzing fewer Twitter posts, noncelebrity Twitter posts, or posts from political leaders versus followers. Analyzing other social media outlets (other than Twitter) would also be worthwhile.

Another subjective aspect of these studies was the LIWC categories selected to represent threat perception (Negative Emotion) and resistance to change (Inhibition-related words). Although we stand by our selections and think that they were the best options available, the availability of alternative categorization schemes may provide different (and potentially better) results. Additionally, there are endless possibilities for motivational constructs that can be studied, both political and nonpolitical, using similar methods. Future research should also examine the extent to which analyzing brief samples of text from larger bodies of text (as we did in Study 2) are differentially predictive of traits other than political affiliation.

Implications

As more individuals communicate via new technology, more short communications arise as a byproduct. Five-hundred million tweets are posted everyday with as many as 6,000 tweets per second (Aslam, 2018; Twitter, 2011). Our data suggest that these tweets may be informative of individuals’ worldviews regardless of their specific intended content (e.g., political vs. nonpolitical). These data are in line with other data that suggest that Twitter data can predict heart disease mortality (Eichstaedt et al., 2015) and the stock market (Bollen, Mao, & Zeng, 2011). Predicting one’s political affiliation from brief text snippets has many implications. One implication is that it enables targeted political advertisements (i.e., advertisements specifically tailored to someone with a specific characteristic). For example, a political campaign can display advertisements designed for persuasive appeal to those with opposing views while directing advertisements intended to bolster existing attitudes to existing constituents. Additionally, to the extent that brief snippets of text reveal political

orientation, scientists can use brief snippets of text to predict election outcomes. In addition to asking people about their mental states, our data suggest that social scientists may be able to learn about individuals indirectly through their short communications (like tweets), which are less likely to contain social desirability bias. The value of determining the motivations behind brief-text transmissions would seem to be growing with each passing week, as national policy is transmitted 140 characters at a time (DeYoung, 2016).

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