Title: Changing Stereotypes of Partisans in the Trump Era

Abstract: Stereotypes of the two parties play an important role in political cognition, and a range of recent studies have examined the content and effects of partisan stereotypes. However, little work has studied change in partisan stereotypes over time. We address this question by comparing data on stereotypes of partisans collected before and after the Trump presidency, a time when we might expect individuals' images of the two parties to undergo significant change. Using a structural topic model, we compare responses to open-ended questions asking respondents to list words describing members of the two parties from 2016 and 2021. We find that partisan stereotypes became less group and issue-based during this period and focused more on personal traits. These results suggest that during the Trump era members of the mass public came to see the parties less as coalitions of groups and more as social groups in their own right, potentially contributing to affective polarization.

Keywords: partisanship; social identity; stereotypes; polarization; affective polarization; structural topic model; political parties

Political scientists and the public have increasingly voiced concerns about the way partisanship divides Americans. One component of this divide is the images and generalizations people have of ordinary Republicans and Democrats, which influence their understanding of the political world. A range of recent studies have measured (Ahler and Sood 2018; Claassen et al. 2021; Rothschild et al. 2019), and shown the effects of (Ahler and Sood 2018; Busby et al. 2021), stereotypes of partisans. However, no work examines changes in partisan stereotypes over time. Party positions and coalitions shift, but stereotypes of social groups can be remarkably stable (Garcia-Marques 2017). Do stereotypes in the mass public change, especially during times of political upheaval?

In a preregistered study, we address this question by comparing data on stereotypes of partisans collected before and after the Trump presidency, a time when we might expect individuals' images of the two parties to undergo significant change. We use data from Rothschild et al. (2019), who in August of 2016 asked 861 respondents from a nationally representative non-probability sample to list "four words that typically describe people who support the Republican Party" and "four words that typically describe people who support the Democratic Party." In August of 2021, we asked 1,200 respondents from a comparable sample the same questions. We then combined these responses together and analyzed them using structural topic modeling (STM), a form of machine learning that identifies themes and frequently co-occurring words, to characterize stereotypes of the two parties. By considering how the prevalence of stereotypes varies across time periods, we evaluate whether and how the respondents' stereotypes of partisans have changed over the past five years. We additionally compare changes in the frequency of commonly used words and in the types of descriptors used, as generated by a hand-coding of the open-ended responses. Overall, we find that Americans' stereotypes of partisans are increasingly rooted in personal traits, a kind of stereotype associated with greater affective polarization. These findings align with other research that finds rising affective polarization and partisan conflict in the United States.

Partisan Identity and Stereotypes

Research in political psychology increasingly conceives of partisanship as a social identity in its own right, comparable in its significance to identities such as race, religion, or gender (Green, Palmquist, and Schickler 2002; Greene 1999, 2004). Among other things, this entails prevalent group-based *stereotypes*—that is, generalizations about the characteristics of groups and their members (Allport 1954; Bordalo et al. 2016). Rothschild et al. (2019) document the existence of stereotypes about supporters of the Democratic and Republican Parties, including their personality and character traits, their other social group memberships, and their political issue priorities. Stereotypes help individuals to simplify and navigate a complex social world, but they may also exacerbate intergroup conflict (e.g., Allport 1954; Eagly and Mladinic 1989). Indeed, holding different mental images of partisans has proven consequential for interparty attitudes and polarization (Ahler and Sood 2018; Busby et al. 2021).

Importantly, stereotypes and their mental accessibility may change due to factors such as the prevailing media environment (Rahn and Cramer 1996; Levendusky and Malhotra 2016), changes in group exemplars or their centrality (Garcia-Marques, Santos, and Mackie 2006), or simply the passage of time (Devine and Elliot 1995; Karlins, Coffman, and Walters 1969). The American political landscape has changed a great deal in just the five years since Rothschild et al. (2019) collected their data. The rise of Donald Trump and his embrace by most of the

Republican Party has changed the most prominent representative of the "Republican" group in a way that exemplar-based theories of stereotypes would expect to change stereotype content (Dasgupta and Greenwald 2001; Garcia-Marques, Santos, and Mackie 2006; Goldman and Mutz 2014), particularly given Trump's overall lack of clear ideological rhetoric. More broadly, demographic and cultural sorting between the two parties (see Mason 2018; Claassen et al. 2021) may have altered perceptions of the parties and their coherence as social groups. On the other hand, many stereotypes prove quite enduring despite social changes (Garcia-Marques et al. 2017), so it remains to be seen how much the public's images of party supporters have shifted during the Trump era. In the sections that follow, we take on this research question, exploring the degree to which Americans' stereotypes of partisans have changed or stayed constant over the last five years.

Research Method

Data

We use data from two sources: Rothschild et al. (2019)'s August 2016 survey of an 861-respondent nationally diverse non-probability sample provided by the firm Research Now (now known as Dynata),[1] and an original survey conducted in late August and early September 2021 of a 1,200-person nationally diverse non-probability sample from the firm Lucid. Both firms use similar "double-opt-in" recruitment procedures to deliver demographically representative samples (Research Now 2014, Lucid 2021); see Appendix B for a discussion of the comparability of the panels. After completing the consent process and an attention check, both samples were asked to "Please write down four words that typically describe people who support

[1] Rothschild et al. (2019) also use a student and mTurk sample. We only use the data collected from Research Now as it is most comparable to the 2021 sample.

the <Republican/Democratic> Party."[2] Respondents were first asked this question with regards to one party, then the other, with the order of parties randomized.[3] For each descriptor, they were asked to give a valence rating from 1 (negative) to 7 (positive). Respondents also completed a set of demographic questions. Question wording was identical in the two surveys. This research was approved by the Institutional Review Boards at <INSTITUTIONS BLINDED FOR REVIEW>.

For the purpose of our main analysis, all words provided by a given respondent are combined into a single text or document. Prior to our analyses, we recoded blank responses, as well as statements like "Don't know," "N/A," and "None", as "Nonresponse." This helps us to evaluate how the absence of stereotypes—whether expressed by affirming a lack of ideas or leaving the question blank—has changed over time.[4] The STM procedures themselves remove stop words ("the", "an", etc.), punctuation, and numbers from the texts. They also put the words into lower case, stem the terms (replacing the words jogging and jog with "jog," for example), and drop terms that occur fewer than 5 times. With all of these pre-processing steps, we rely on the defaults in STM, parallel to the decisions made in Rothschild et al. (2019). In our secondary discussion of word frequency, we recode a number of close synonyms, using the same approach and an updated list of synonyms from Rothschild et al. (2019).

Analysis

Structural topic modeling (STM) uses a form of machine learning to describe the co-occurrence of words within a set of documents—in this case, the combined open-ended

[2] Respondents were provided with four blanks but were not forced to fill any of them.
[3] This is just one type of text one could examine. Other possibilities include tweets referencing Republicans and Democrats and stereotype categorizations of individuals with different attributes. We use our method here because it closely matches work in psychology on other stereotypes (e.g., Eagly and Mladinic 1989) and captures respondents' stereotypes in a more direct way than alternatives.
[4] For more details on recoding procedures, see the appendix.

responses from each respondent. STM identifies words that tend to appear together within documents and organizes them into topics; thus, researchers can gain a detailed sense of the patterns and themes in survey respondents' thoughts with minimal assumptions (Roberts et al. 2014). In the present study, we combine responses from both surveys into a single corpus of documents, to precisely compare the words/topics used in 2016 compared to 2021. We produce two topic models, one for stereotypes of Democrats and one for stereotypes of Republicans. Prior to our analysis, we preregistered our use of STM and subsequent analyses.[5]

An STM cannot determine the "best" number of topics; researchers must select a number of topics for the model (Roberts et al. 2014). However, the method provides a number of statistical metrics by which to compare candidate models with different numbers of topics (Blei, Ng, and Jordan 2003; Taddy 2012). After deciding on the number of topics, researchers can assess different model specifications based on two main quantities: (1) *semantic coherence*, the co-occurrence of high-probability words in a topic within the documents, and (2) *exclusivity*, a low probability that the high-probability words from a given topic appear among the top words for any other topic. Beyond this, human interpretation and judgment are still required to ensure that the chosen model's topics make theoretical sense.

For the current study, we examined potential models for each party with between 5 and 75 topics. We used a sparse additive generative (SAGE) method, which produces models with greater semantic coherence when using documents of short length such as ours (Eisenstein, Ahmed, and Xing 2011). After identifying a narrower range of topic numbers with the best statistical values, we examined those possibilities more closely and chose two or three

[5] Available at https://osf.io/nyv6e/?view_only=120157aac70d49268fa038d2fdd8720e

alternatives for each party. For each of these, we generated a set of six model specifications and focused on those with the highest semantic coherence and exclusivity values. Based on our collective reading of the topics themselves and exemplar documents, we selected the topic models that provide the most sensible description of our data. See Appendix F for more explanation and detailed results from each step of this process.

STM also allows the inclusion of covariates—characteristics of the individual documents—which may then be associated with the use of different topics in subsequent analyses. We focus on prevalence covariates, which permit the frequency or amount of a topic to vary according to that variable. In other words, using a prevalence covariate for year allows 2016 respondents to talk about each topic more or less than 2021 respondents do.[6] Therefore, we included survey-year as a prevalence covariate in order to evaluate the possibility that the frequency of a given topic has changed with time. We interacted the survey-year with indicator variables for partisanship (Republican, Democrat, Independent, with leaners coded as partisans) to determine if any changes in topic use depend on the partisanship of the respondent. We also included demographic variables (income, education, gender, race, ethnicity, age, political interest, and political knowledge)[7] as prevalence covariates in these models.

We evaluate prevalence covariates in a way generally consistent with traditional tests of significance. STM produces estimates of how the frequency of topic use differs by a given prevalence covariate, and these estimates include confidence intervals that incorporate the uncertainty from the topic modeling process. As such, determining whether survey-year

[6] Our analysis plan included survey-year as a content covariate. However, this prevents the retrieval of the exclusivity metric during the initial STM analysis. Because exclusivity is key to choosing the topic models, we elect not to include the content covariate.
[7] Both surveys used the same questions to measure political interest and knowledge. Demographic variables were re-coded so that they matched in both samples.

influences the frequency of a given topic involves evaluating the statistical significance of differences in topic use by survey-year (interacted with partisanship as mentioned).

As a check on these results, we draw on an unpublished inductive hand-coding of Rothschild et al. (2019)'s data. This coding inductively generated a list of seven categories from the descriptors used by respondents in Rothschild et al. (2019), and then used these to categorize all descriptors that were mentioned by at least three respondents (Myers 2019). We apply these codes to the 2016 and 2021 samples, coding any new terms that appear in the 2021 sample but not the 2016 sample using the same inductive coding procedure. For each category, we compare the proportion of respondents in each sample who use at least one descriptor from the category using a difference of proportion test. Finally, we assign a "type" to each respondent based on the most frequent category among their responses. This analysis is presented in the appendix.

Results

We begin our main analysis by presenting the stereotype topics for Democrats and Republicans. For both parties, our model selection process yielded 8 topics.[8] Table 1 shows the Democratic topics as well as the proportion of responses that each topic represents. Following Rothschild et al. (2019), we report FREX words—that is, words that appear frequently within each topic and are most exclusive to that topic. We supplement these results with our reading of the exemplar documents most closely associated with each topic, to gain a richer understanding of the thoughts articulated by respondents. (The top 10 exemplar documents for each topic are provided in the appendix.)

Topic	FREX words	Proportion
1	stupid, mean, idiot, selfish, uninform, unrealist, evil	.072

[8] The matching number of topics is coincidental.

2	<NONRESPONSE>, conserv, arrog, loud, abort, spender, posit	.306
3	socialist, pro, young, free, minor, govern, liber	.176
4	class, middl, poor, union, peopl, left, blue	.084
5	lazi, liar, dont, dumb, stubborn, rich, fake	.060
6	honest, smart, equal, trustworthi, kind, hope, support	.099
7	good, great, like, nice, cool, joe, biden	.079
8	open, care, help, inclus, intellig, peac, fair	.123

Table 1. Democratic Stereotype Topics

In line with findings from Busby et al. (2021), many of these topics cohere around distinct themes related to partisans' individual characteristics, the groups to which they belong, and political issue priorities. Topics 6 and 8, for example, describe supporters of the Democratic Party in terms of positive individual traits such as "honest", "smart", "open-minded", and "caring", whereas Topics 1 and 5 list negative traits like "stupid" and "lazy". Topic 4 emphasizes a number of groups associated with the Democratic coalition—the middle class, the poor, and unions—and Topic 3 similarly references young people and (in the exemplars) minorities. Issue-based language does not appear as prominently in the FREX words, though Topic 3 includes mentions of big government and socialism. The exemplars for that topic include more specific terms such as "taxes", "entitlements", and "welfare". The four trait-focused topics occupy a large share of responses—0.354—in accordance with Rothschild et al. (2019)'s observation that these kinds of stereotypes tend to be the most common among the public.

Notably, we also observe a lack of substantive answers from many survey participants. Topic 2, which is almost exclusively responses coded as nonresponse (e.g., leaving the space blank or saying "don't know"),[9] takes up the single largest topic proportion at .306. Topic 7, while it includes more actual responses, tends to be relatively vague or unsophisticated (e.g., referencing Joe Biden or using generic descriptors such as "good" or "great"). The presence of these topics in the model suggests that, while many respondents can call to mind specific and detailed thoughts about Democratic supporters, many others prove unable or unwilling to do so. This aligns with perennial findings concerning the low political sophistication of many voters (Converse 1964; Kinder and Kalmoe 2017).

Table 2 presents stereotype topics and proportions for Republican supporters. As with Democrats, topics expressing positive and negative personal traits occupy a large proportion of responses, such as "honest" and "loyal" in Topic 2, "greedy" and "selfish" in Topic 4. Topic 3 highlights groups associated with the party, such as whites and the wealthy, though these are mixed with more trait-based terms like "stubborn" and "biased". Topics 5, 6, and 7 mention groups as well (e.g., the middle class, older people, Christians, and rural residents), but these are mixed with more issue- or value-based terms like "hard work", "freedom", and "pro life". This, too, coheres with previous findings from Rothschild et al. (2019), who find that group- and issue-focused responses often occur together. We also see a pattern of nonresponse (Topic 1) and vague responses (Topic 8) similar to what we find for Democratic stereotypes.

Topic	FREX words	Proportion
1	<NONRESPONSE>, peopl, dont, opinion, liber, polit, republican	.310
2	care, smart, honest, loyal, help, patriot, american	.118
3	rich, white, male, stubborn, wealthi, bias, self	.091

[9] The STM algorithm lists six FREX words for each topic, even topics overwhelmingly dominated by a single "word". All ten of the exemplar responses that best characterize this topic contain only nonresponses; similarly, nine of ten exemplar responses for Republican Topic 1 contain only nonresponses.

4	greedi, selfish, racist, liar, stupid, dumb, ignor	.186
5	pro, life, rural, gun, christian, conserv, govern	.145
6	middl, educ, class, hardwork, freedom, strong, busi	.043
7	old, religi, less, law, upper, collar, brainwash	.047
8	good, like, bad, cool, awesom, nice, great	.060

Table 2. Republican Stereotype Topics

We turn next to our primary research question: Has the content of partisan stereotypes changed over the last five years? As mentioned, we use survey-year as a prevalence covariate in our STMs, which enables us to test whether the use of words from different topics differs between 2016 and 2021. Figure 1 plots the use of the topics described above in both 2016 and 2021, broken out by respondent partisanship. The differences between the surveys can be read essentially as a difference in averages —for example, among Democrats we see a .0826 increase in the proportion of responses coming from Topic 8, and a smaller increase of the same among Republicans. Alongside similar increases in the use of terms from Topic 6, these results suggest an overall growth in trait-based stereotypes over time. This accords with the trend theorized by Busby et al. (2021), in which Americans have personalized their partisanship and treat it as a social identity in its own right. Meanwhile, we see decreases in Topics 3 and 4—which largely embody left-wing and marginalized groups within the Democratic coalition—among Democrats, as well as a decrease in Topic 3 among Republicans. Coalition-based thinking about Democratic Party supporters thus seems to have declined, though we do observe a marginally significant *increase* in Republicans' use of class-based language in Topic 4 to describe outpartisans.

Turning to the proportions and shifts for Republican topics, a similar pattern emerges. In 2021 compared to 2016, supporters of both parties use terms from Topic 5 less often. This topic heavily references what we might call the "pre-Trump" Republican coalition, including groups like Christians and the wealthy as well as issues like abortion and gun rights. At the same time, we see increases in Topic 2 with its references to characteristics such as patriotism, honesty, and loyalty. This suggests, firstly, another decline in group-based partisan stereotypes alongside a growth in trait-based stereotypes. The shift appears, as well, to reflect an increased emphasis on patriotism (perhaps nationalism) over more traditional forms of group politics—particularly in how Republicans see themselves, evidenced by their much larger Topic 2 increase of .257.

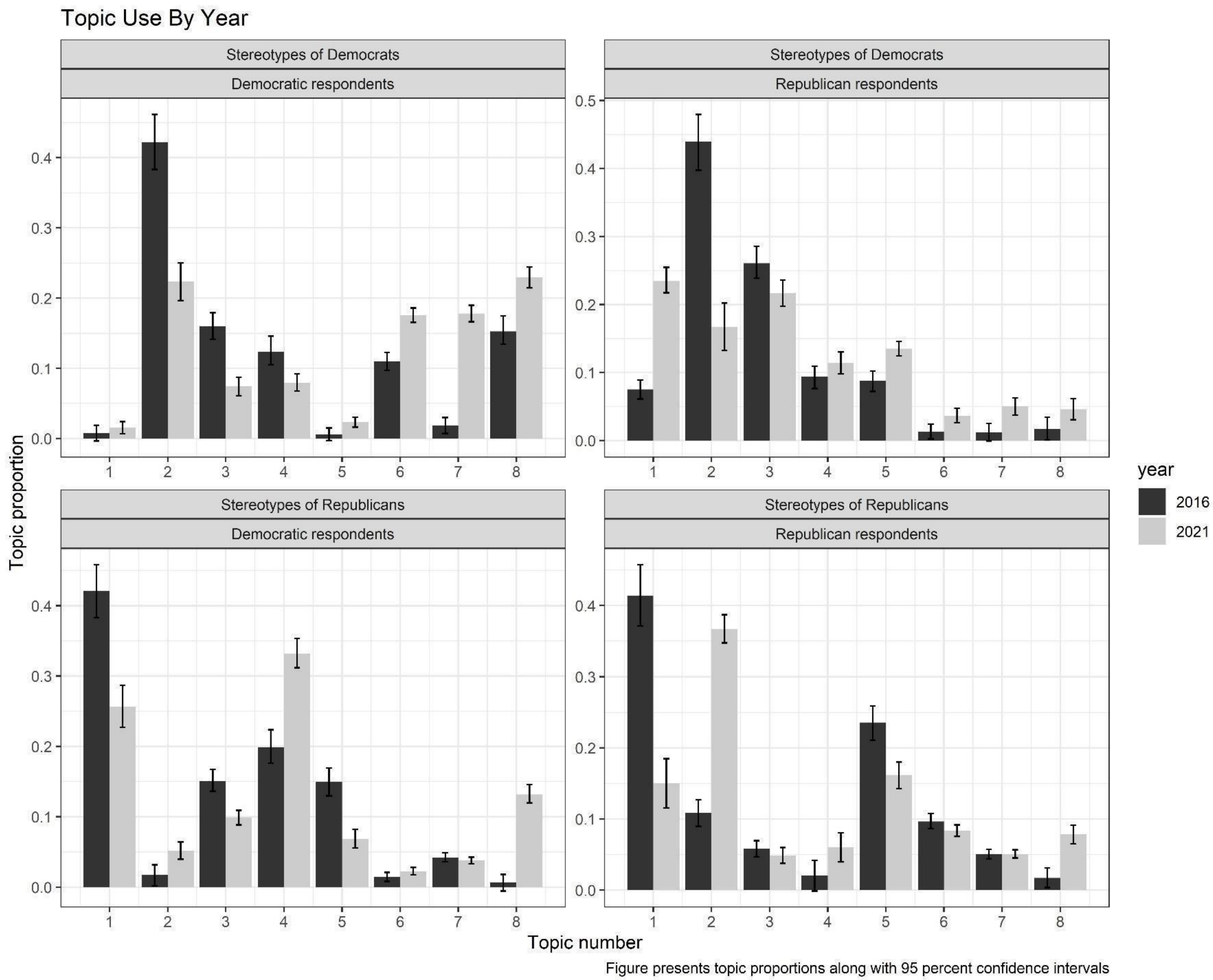
As with Democrats, we also see a substantial decrease across years in nonresponse (Topic 1), alongside an increase in generic positive language (Topic 8). Overall, then, even among individuals without many concrete top-of-the-head ideas about partisans, those surveyed in 2021 prove more likely than those in 2016 to say *something* rather than leave the stereotype question blank or say "don't know". To ascertain whether this stems from greater attentiveness to the survey among the 2021 sample—which might suggest a panel effect skewing our other results—we examine whether the relationships between survey-year and topic proportions differ for respondents who passed versus failed our attention check (see the appendix for details). In sum, we find very few significant differences and conclude that differences in the use of more substantive stereotype topics do *not* result from the two samples approaching the task differently.

Results for both parties tell a story of more strongly trait- or identity-based thinking about partisanship over time—a continuation of trends observed by Busby et al. (2021) and findings from other studies of polarization (e.g., Iyengar, Sood, and Lelkes 2012; Mason 2018).

Simultaneously, images of partisans as members of other groups or as prioritizing certain political issues appear to have declined in the last five years, though such ideas still come to mind for many respondents. In sum, what Busby et al. (2021) call the *partisan-identity* perspective on partisanship has continued to gain popularity among the public, while the *coalitional* and *instrumental* perspectives have further diminished.[10]

[10] Results reported in Appendix A that use a hand-coding of descriptors to classify respondents' stereotype return similar results - the proportion of respondents holding "trait" stereotypes increases, while the proportion holding "group" stereotypes decreases.

Figure 1.Topic Proportions and Shifts Over Time



Discussion and Conclusions

Our results reveal that, while some changes have occurred in the content of partisan stereotypes, much has stayed the same. Many of the group-, issue-, and trait-based images observed in 2016 by Rothschild et al. (2019) remain present in our 2021 sample. The American public's ideas about the parties thus continue to be complex and multifaceted, and reflect disparate conceptions of partisanship discussed by political scientists.

The content has shifted, however, in terms of which ideas Americans call to mind most easily. Trait stereotypes—already the most common type in 2016 (Rothschild et al. 2019)—have become even more prevalent, suggesting that partisanship is increasingly viewed as a social identity in itself, with its own set of associated characteristics and value judgments. The magnification of this trend proves most evident in Republicans' images of their own party, with the single greatest change in stereotype prevalence centered on their increased use of words like "patriots", "patriotic", "loyal", and "Americans" alongside a number of more general positive traits. Though we cannot say for certain with these data, it strikes us as plausible that Donald Trump's rise to power within the party and his increased promotion of nationalistic ideas have exerted an influence here.

Stereotypes may thus shift in response to even short-term changes in the political environment. Future work, however, should look more deeply into this potentially causal connection, as it holds far-reaching implications for future democratic functioning. The continued growth of sectarian and personalized thinking about partisanship may, as noted by Busby et al. (2021), presage greater polarization in the years to come.

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