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RESEARCH NOTE

Changing stereotypes of partisans in the Trump Era

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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 in the 2021 sample are less group- and issue-based and focused more on personal traits. These results suggest that, during the Trump era, members of the mass public came to see the parties in more personalized, character-focused terms, potentially contributing to affective polarization.

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

Political scientists have increasingly voiced concerns about the way partisanship divides Americans. One component of this divide is the images people hold of ordinary Republicans and Democrats, which influence their understanding of the political world. Recent studies have shown the effects of stereotypes of partisans (Ahler and Sood, 2018; Rothschild *et al.*, 2019). 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 *et al.*, 2017). Do stereotypes in the mass public change, especially during times of political upheaval?

In a preregistered study, we compare data on stereotypes of partisans collected before and after the Trump presidency, during which we might expect images of partisans to undergo significant change. In August 2016, Rothschild *et al.* (2019) asked 861 respondents from a representative non-probability sample to list "four words that typically describe people who support" each party. In August 2021, we asked 1200 respondents from a comparable sample the same questions. We combine these responses and use structural topic modeling (STM) to characterize respondents' stereotypes of partisans, evaluating whether and how they have changed over the past five years. Additionally, we compare changes in commonly used words and types of descriptors, generated by hand-coding of the open-ended responses. Overall, Americans' stereotypes of partisans are increasingly rooted in personal traits, associated with greater affective polarization.

1. Partisan identity and stereotypes

Research in political psychology conceives of partisanship as a social identity in its own right, comparable in its significance to race or religion (Green *et al.*, 2002; Greene, 2004; Mason, 2018). This entails *stereotypes*—generalizations about the characteristics of groups and their members (Allport, 1954; Bordalo *et al.*, 2016). Rothschild *et al.* (2019) document 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 navigate a complex social world, but they may also exacerbate intergroup conflict (e.g., Allport, 1954; Eagly and Mladinic, 1989). Holding different mental images of partisans has proven consequential for inter-party attitudes and polarization (Ahler and Sood, 2018; Busby *et al.*, 2021).

Stereotypes and their mental accessibility may change due to the prevailing media environment (Rahn and Cramer, 1996; Goldman and Mutz, 2014), changes in group exemplars (Garcia-Marques *et al.*, 2006), or simply the passage of time (Karlins *et al.*, 1969; Devine and Elliot, 1995). The American political landscape has changed a great deal since 2016. The rise of Donald Trump and his embrace by most of the Republican Party, alongside conflict within the Democratic Party culminating in Joe Biden's victory, have changed the prominent exemplars of the two parties, potentially altering stereotype content (Goldman and Mutz, 2014). Demographic and cultural sorting (Mason, 2018) may have changed perceptions of the parties, their characteristics, and their core values. Many stereotypes endure despite social changes (Garcia-Marques *et al.*, 2017), however. We therefore explore the degree to which stereotypes of partisans have changed or stayed constant.

2. Research method

2.1 Data

Our preregistered analysis[1] uses two data sources: Rothschild *et al.* (2019)'s August 2016 survey of a representative non-probability sample ($N = 861$) provided by Research Now (now called Dynata), and an original survey conducted in late August and early September 2021 of a representative non-probability sample ($N = 1200$) provided by Lucid. Both firms use "double-opt-in" recruitment procedures to deliver demographically representative samples (Research Now, 2014; Lucid, 2021); see Appendix B regarding panel comparability. Both samples were asked: "Please write down four words that typically describe people who support the <Republican/Democratic> Party."[2] Respondents answered this question with respect to one party, then the other, with the order randomized, followed by a set of demographic questions.

For our main analysis, all words provided by a given respondent are combined into one document. We recode blank responses, as well as statements like "Don't know," "N/A," and "None," as "Nonresponse," to evaluate how the absence of stereotypes has changed over time.[3] STM procedures remove stop words ("the", "an", etc.), punctuation, and numbers from the texts. They put the words into lower case, stem them (replacing "jogging" and "jogs" with "jog," for example), and drop terms that occur fewer than five times. These pre-processing steps match those in Rothschild *et al.* (2019). In our secondary analysis of word frequency, we recode close synonyms, using the same approach and an updated list from Rothschild *et al.* (2019).

2.2 Analysis

STM uses machine learning to describe the co-occurrence of words within a set of documents—in this case, the combined open-ended responses from each respondent. STM identifies words that tend to appear together within documents and organizes them into topics, giving researchers a detailed sense of the patterns in respondents' thoughts with minimal assumptions (Roberts

[1]https://osf.io/nyv6e/?view_only=120157aac70d49268fa038d2fdd8720e

[2]Respondents were provided four blanks where they could write as much as they chose but were not forced to fill any. The questions are worded in terms of party supporters to emphasize ordinary people who affiliate with the parties rather than, for example, party elites.

[3]For details on recoding procedures, see Appendix A.

et al., 2014). We combine responses from both surveys into a single corpus of documents, to compare the words/topics used in 2016 and 2021. We produce two topic models, one for stereotypes of Democrats and one for stereotypes of Republicans.

STM cannot determine the "best" number of topics; researchers must select that for the model (Roberts *et al.*, 2014). However, the method provides metrics to compare candidate models with different numbers of topics (Blei *et al.*, 2003; Taddy, 2012), primarily (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 one topic appear among those for any other topic. Human interpretation and judgment are still required to ensure the chosen model's topics make theoretical sense.

We examined potential models for each party, between 5 and 75 topics, using a sparse additive generative method, which produces models with greater semantic coherence for documents of short length (Eisenstein *et al.*, 2011). After identifying a narrower range of topic numbers, we examined those possibilities more closely and chose two or three alternatives for each party. For each of these, we generated six model specifications and focused on those with the highest semantic coherence and exclusivity. 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 H for more explanation and detailed results from each step of this process.

STM allows the inclusion of covariates—characteristics of individual documents—which may 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.[4] Therefore, we included survey-year to test whether the frequency of a given topic has changed with time. We interacted 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 demographics (income, education, gender, race, ethnicity, age, political interest, and political knowledge)[5] as prevalence covariates.

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 each prevalence covariate, and these estimates include confidence intervals incorporating uncertainty from the topic modeling process. We evaluate the statistical significance of differences in topic use by survey-year, interacted with partisanship as mentioned.

As a check on these results, we also hand-coded responses, inductively generating a list of seven categories, then used these to categorize all descriptors mentioned by at least three respondents. We briefly discuss these results below, and describe this procedure and its results in detail in Appendix A.

3. Results

We first present the stereotype topics for Democrats and Republicans. For both parties, our model selection process yielded eight topics.[6] 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—those 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

[4]Our analysis plan included survey-year as a content covariate. However, this prevents the retrieval of exclusivity during the STM analysis. Because exclusivity is key to choosing the topic models, we elect not to include the content covariate.

[5]Both surveys used the same questions to measure political interest and knowledge. Demographic variables were re-coded so they matched in both samples.

[6]The matching number of topics is coincidental.

Table 1. Democratic stereotype topics

Topic	FREX words	Exemplars	Proportion
1. Bad people	stupid, mean, idiot, selfish, uninform, unrealist, evil	evil selfish greedy lying; gullible hateful uneducated naive	0.072
2. Nonresponse	<NONRESPONSE>, conserv, arrog, loud, abort, spender, posit	<NONRESPONSE> <NONRESPONSE> <NONRESPONSE> <NONRESPONSE>; <NONRESPONSE> <NONRESPONSE> <NONRESPONSE> <NONRESPONSE>	0.306
3. Liberal coalition	socialist, pro, young, free, minor, govern, liber	liberal elitist welfare taxes; liberals young minorities underprivileged	0.176
4. Class interests	class, middl, poor, union, peopl, left, blue	working class union members gov't workers blue collar; middle class poor blacks women	0.084
5. Dishonest and lazy	lazi, liar, dont, dumb, stubborn, rich, fake	fake dishonest dumb ignorant; liars fake evil gross	0.060
6. Smart and honest	honest, smart, equal, trustworthi, kind, hope, support	smart logical educated right; honest thoughtful sincere trustworthy	0.099
7. Insincere positive	good, great, like, nice, cool, joe, biden	joe biden democratic party democrat party democrat party; extremely interested extremely interested extremely interested extremely interested	0.079
8. Caring and inclusive	open, care, help, inclus, intellig, peac, fair	open minded caring environmental focused helping others; compassionate inclusive caring progressive	0.123

associated with each topic, to gain a richer understanding of respondents' thoughts. Two exemplar documents for each topic are provided in the table, from the top 10 exemplar documents for each topic listed in Appendix F. For ease of reference, we also give each topic a substantive name based on our subjective reading of the FREX words and exemplars.

In line with findings from Busby *et al.* (2021), many topics cohere around partisans' individual characteristics, the groups to which they belong, or political issue priorities. *Smart and Honest* and *Caring and Inclusive* describe supporters of the Democratic Party with positive traits like "thoughtful," "open-minded," and "helping others," whereas *Bad People* and *Dishonest and Lazy* list negative traits like "stupid" and "fake." *Class Interests* emphasizes groups associated with Democrats—the middle-class, the poor, and unions. *Liberal Coalition* similarly references young people and (in the exemplars) minorities, as well as big government and socialism. The four trait-focused topics occupy a large share of responses—0.354—in accordance with Rothschild *et al.* (2019)'s observation that these stereotypes tend to be most common.

Notably, we also observe a lack of substantive answers from many participants. Topic 2, which is almost exclusively coded as nonresponse (e.g., leaving the space blank or saying "don't know"),[7] occupies the single largest topic proportion at 0.306. The *Insincere Positive* topic, while including more actual responses, tends to be vague (e.g., referencing Biden or generic descriptors such as "good" or "great"), and likely reflect patterns of insincere responding by a small number of survey respondents (Kennedy *et al.*, 2021). The presence of these topics in the model suggests that, while many people can call to mind detailed thoughts about Democratic supporters, others prove unable or unwilling to do so.[8] Below and in the appendix, we discuss supplementary analyses to address both tendencies across samples.

Table 2 presents stereotype topics and proportions for Republican supporters. As with Democrats, topics expressing positive and negative traits occupy a large share of responses,

[7]All 10 of the exemplar responses that best characterize this topic contain only nonresponses, so the other five FREX words contribute little to this topic or the similar Republican topic.

[8]With respect to nonresponse, 82 percent of respondents provided an answer in at least one field for each stereotype question.

Table 2. Republican stereotype topics

Topic	FREX words	Exemplars	Proportion
1. Nonresponse	<NONRESPONSE>, peopl, dont, opinion, liber, polit, republican	<NONRESPONSE> <NONRESPONSE> <NONRESPONSE> <NONRESPONSE>; <NONRESPONSE> <NONRESPONSE> <NONRESPONSE> <NONRESPONSE>	0.310
2. Caring patriots	care, smart, honest, loyal, help, patriot, american	conservative loyal honest trustworthy; americans honest loyal hard working	0.118
3. Rich White men	rich, white, male, stubborn, wealthi, bias, self	rich white male strict taxes; white farmers wealthy male	0.091
4. Selfish bigots	greedi, selfish, racist, liar, stupid, dumb, ignor	nazis trump supporters racists idiots; racist liars greedy selfish	0.186
5. Traditional coalition	pro, life, rural, gun, christian, conserv, govern	realistic nonconformists conservative responsible; conservative right leaning frugal staunch	0.145
6. Class interests	middl, educ, class, hardwork, freedom, strong, busi	middle class middle class middle class middle class; strong no nonsense middle class employed	0.043
7. Religious traditionalists	old, religi, less, law, upper, collar, brainwash	conservative upright religious old fashioned; old conservative selfish religious	0.047
8. Insincere positive	good, like, bad, cool, awesom, nice, great	very good very good very good very good; extremely interested extremely interested extremely interested extremely interested	0.060

such as "honest" and "loyal" in *Caring Patriots*, "greedy" and "racist" in *Selfish Bigots*. *Rich White Men* highlights groups associated with the party, along with traits like "stubborn" and "biased." *Traditional Coalition*, *Class Interests*, and *Religious Traditionalists* 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 coheres with Rothschild *et al.* (2019), who find that group- and issue-focused responses often occur together. We also see patterns in *Nonresponse* and *Insincere Positive* similar to Democratic stereotypes.

3.1 Changing partisan stereotypes?

Has the content of partisan stereotypes changed over the last five years? Figure 1 plots the use of the above topics in 2016 and 2021, by respondent partisanship. We see about the same amount of overall change for stereotypes of both parties, as well as among Democratic and Republican respondents.[9] Focusing first on stereotypes of Democrats, differences between surveys can be read as a difference in averages—for example, among Democrats we see a 0.0826 increase in the proportion of responses from *Caring and Inclusive*, and a smaller increase of the same among Republicans. Alongside similar increases in use of terms from *Smart and Honest*, these results suggest growth in trait-based stereotypes over time. Meanwhile, we see decreases in *Liberal Coalition* and *Class Interests*—left-wing and marginalized groups within the party—among Democrats, as well as a decrease in *Liberal Coalition* among Republicans. Group-based thinking about Democratic supporters has declined, though we observe a marginal increase in Republicans' use of words from *Class Interests*.

Turning to proportion shifts for Republican topics, a similar pattern emerges. In 2021, compared to 2016, supporters of both parties use fewer terms from *Traditional Coalition*, which reflects the "pre-Trump" Republican Party, including groups like Christians and the wealthy as well as issues like abortion and gun rights. We simultaneously see increases in *Caring Patriots*

[9]Across all topics, the average change in usage was 8 percentage points. We see similar amounts of change across stereotypes of both parties by both groups of partisans.

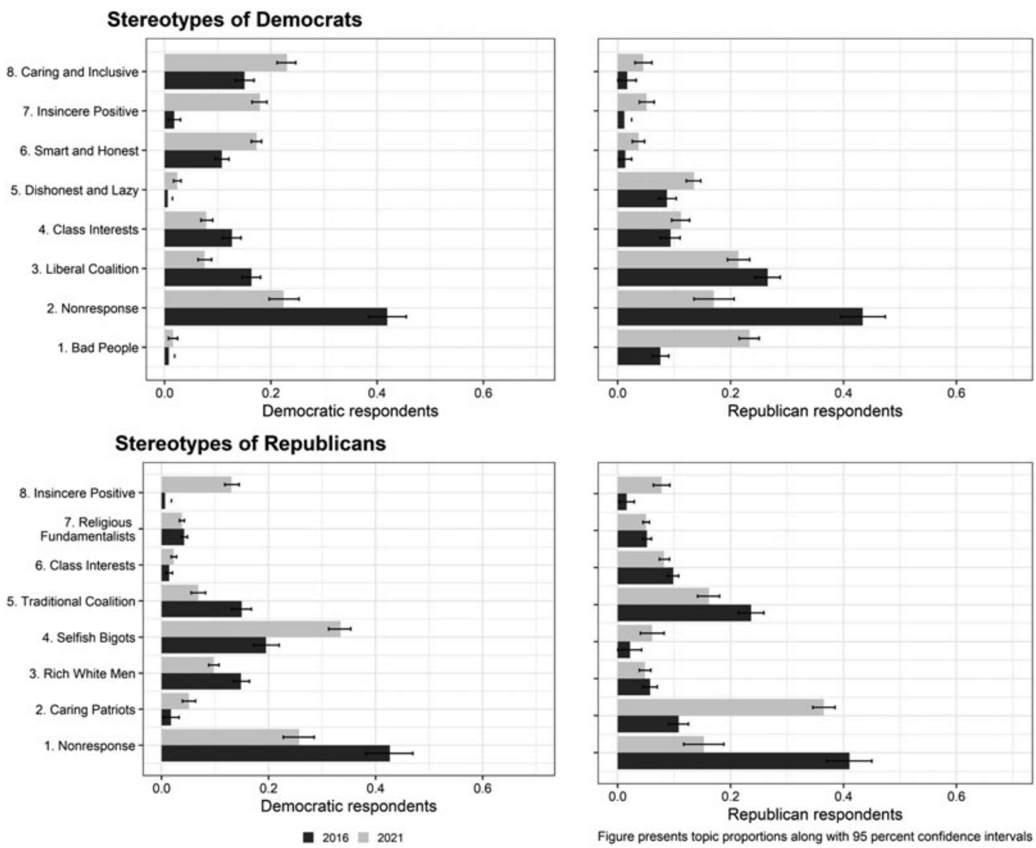

Figure 1. Topic proportions and shifts over time.

with its references to values such as honesty and loyalty. This suggests another decline in group-based partisan stereotypes alongside 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 *Caring Patriots* increase of 0.257.

Results for both parties suggest a story of increased trait- or character-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 *et al.*, 2012). 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. The results of our auxiliary hand-coding of responses largely support this conclusion. Because of space constraints, we report this analysis in Appendix A. Briefly, these results find reductions in group- and issue-based descriptors and an increase in trait descriptors (Tables A2–A5). We also categorize respondents by the type of descriptors they use, and find that the proportion using ideology, group, and issue descriptors is lower in 2021 than in 2016, but the proportion using trait descriptors is higher (Tables A6–A9).

One alternative explanation for these over-time patterns is that they result from differences in the two samples, or changes in the way participants in non-probability "double opt-in" samples responded to our stereotype questions. Changes in the proportion of the *Nonresponse* and *Insincere Positive* categories suggest this is possible. We thus conduct three supplementary analyses. To account for demographic differences between samples, Appendix B reports results after reweighing both samples separately to census benchmarks; we find no substantive changes as a result.[10] Appendix C examines differences between respondents who pass or fail attention checks; we find a slightly higher level of failure in the 2021 sample, but also that topic usage varies little between those who pass and those who fail. Finally, to address concerns that these kinds of samples have seen an increase in what Kennedy *et al.* (2021) term "insincere" respondents, we follow those authors' procedure to identify insincere respondents using an unrelated open-ended question (Appendix G). We do find an increase in the proportion of insincere respondents in 2021, though in both years they make up a small percentage of the sample (1.4 percent in 2016, 5.6 percent in 2021). We re-estimate the topic proportions after removing these respondents and, again, find little substantive difference from our main results. Even with these auxiliary analyses, we cannot rule out the possibility that respondents in 2016 and respondents in 2021 approach these questions in a fundamentally different way unrelated to attention, the demographics used in the weighting, or response sincerity; readers who remain skeptical of the *comparison* may still find value in the results for each cross-section individually.

4. Discussion and conclusions

Our results reveal that, while 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 continue to be multifaceted and reflect disparate conceptions of partisanship discussed by political scientists, yet we can identify common clusters of attributes.

The content has shifted, however, in terms of which clusters Americans call to mind most easily. Trait stereotypes—already the most common type in 2016 —appear even more prevalent, suggesting that partisanship is increasingly viewed as a social identity in itself, with its own associated characteristics and value judgments. 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 "patriotic," "loyal," and "Americans." Though we cannot say for certain with these data, this strikes us as a plausible effect of Donald Trump's rise to power and nationalistic rhetoric. More broadly, perceptions of a growing "us-versus-them" mentality in partisan politics may have engendered more identity-based thinking.

Importantly, the shifts we observe may not *solely* reflect increases in partisan-identity mindsets. Trait-based stereotypes may also relate to value- and issue-based ideas linked to partisanship (Hayes, 2005; Clifford, 2020, 2022); indeed, conflict over fundamental values increasingly drives affective polarization (Enders and Lupton, 2021). However, in our data, we fail to find increases in directly issue-focused themes. Political values, moreover, may be influenced by partisan and other social identities (Connors, 2020), further underlining the importance of partisan identity *per se*. We cannot, however, dispositively disentangle the role of identity and values in our analysis; it seems likely that both matter when determining how ordinary Americans think about the individual traits of rank-and-file partisans.

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 presage greater polarization in the years to come.

Supplementary material. The supplementary material for this article can be found at https://doi.org/10.1017/psrm.2023.30. To obtain replication material for this article, https://doi.org/10.7910/DVN/SCEL5P

Competing interest. None.

[10]We thank an anonymous reviewer for this suggestion.

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