**Online Appendices for Changing Stereotypes of Partisans in the Trump Era**

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**Appendix A: Hand-Coding Analyses**

In addition to the STM results presented in the main text, we conducted several analyses that compare the raw frequencies of descriptors used and that use hand-coding to classify the type of stereotype reflected in each participant’s responses. Before conducting these analyses, we performed a limited amount of strict synonym recoding, as in Rothschild et al. (2019). This process is restricted to harmonizing terms that are clear and unambiguous equivalents—such as replacing “Whites”, “White people”, and “people who are White” with “Whites” or collapsing “President Trump”, “President Donald Trump”, and “Donald Trump” to “Donald Trump”. Merging synonyms in this way enables us to gauge the prevalence of discrete *ideas* among respondents, not just particular word choices. This process uses the list of synonyms used in Rothschild et al (2019) with some additional terms (agreed upon by all three authors) based on a reading of samples from the text data.

*A.1 Analyses of Word Frequency*

First, we list the most frequent words from each year for stereotypes of Republicans and stereotypes of Democrats and then break these out by the partisanship of the respondent. We next test for descriptors whose frequency is significantly more or less common in the 2021 sample. We limit this test to descriptors that are listed by 10 or more respondents across the two samples. Following the logic of Lijffijt et al. (2016), we conduct a difference of proportion test to compare the proportion of respondents in each sample who list each word for each party, and list those words whose frequency is significantly different (*α* = .05), as well as those words whose frequency is significantly different between years among subsamples of Democrats, Republicans, and Independents. To see if the overall affective charge of these descriptors has changed over time, we calculate the mean positivity rating for each respondent for each party, and then compare the mean respondent-level positivity towards Republicans and Democrats across time, and among partisan sub-samples across time.

Table A1 shows the descriptors used by the highest percentage of respondents for Republicans and Democrats in the two samples. Tables A2 and A3 repeat this for the most frequently used descriptors used by Democrats to describe the two parties (Table A2) and by Republicans to describe the two parties (Table A3). In general, there is a great deal of overlap between the two lists of frequent words.

Tables A1-A3 also show the mean positivity of descriptors in each year for each stereotype. In the full sample (Table A1), positivity ratings were not significantly different across years, (*d* = .04, *p* = .39 for descriptors of Democrats; *d* < .01, *p* = .948 for descriptors of Republicans). However, this obscures changes among partisan groups. Democrats’ rating of their descriptors of Democrats increased significantly (*d* = .22, *p* < .001), while Republicans’ rating of their descriptors of Democrats decreased by a similar amount (*d* = .21, *p* = .004). Democrats’ ratings of their descriptors of Republicans were largely unchanged (*d* = .04, *p* = .468), but Republicans’ ratings of their descriptors of Republicans were significantly more positive (*d* = .36, *p* < .001). This provides further evidence of increased polarization in partisans’ stereotypes of each other.

| **Descriptors used by Full Sample** | **Descriptors of Democrats** | | **Descriptors of Republicans** | |
| --- | --- | --- | --- | --- |
| **2016 Sample** | **2021 Sample** | **2016 Sample** | **2021 Sample** |
| **Most frequent response (% of respondents)** | <Non-Response>  (50.4%) | <Non-Response>  (25.1%) | <Non-Response>  (50.0%) | <Non-Response>  (25.0%) |
| **2nd** | Liberal  (33.8%) | Liberal  (22.4%) | Conservative  (30.4%) | Conservative  (17.1%) |
| **3rd** | Caring  (7.0%) | Caring  (11.0%) | Rich  (16.5%) | Rich  (8.7%) |
| **4th** | Open Minded  (6.4%) | Smart  (7.9%) | White  (10.2%) | Smart  (7.6%) |
| **5th** | Poor  (5.8%) | Ignorant  (6.9%) | Prejudiced  (7.1%) | Ignorant  (7.4%) |
| **6th** | Minorities  (4.7%) | Open-Minded  (6.3%) | Religious  (5.8%) | Prejudiced  (7.0%) |
| **7th** | Ignorant  (4.6%) | Good  (5.5%) | Senior Citizens  (5.1%) | Self-Interested  (6.8%) |
| **8th** | Youth  (3.9%) | Friendly  (5.0%) | Ignorant  (4.9%) | Mean  (5.2%) |
| **9th** | Smart  (3.5%) | Honest  (3.9%) | Closed-Minded  (3.6%) | Good  (5.0%) |
| **10th** | Educated  (3.4%) | Equality  (3.5%) | Self-Interested  (3.5%) | Patriotism  (4.8%) |
| **Mean Positivity**  **(95% Conf Int)** | 4.55  (4.41, 4.67) | 4.64  (4.52, 4.75) | 4.36  (4.23, 4.50) | 4.36  (4.24, 4.47) |

**Table A1. Most Frequent Descriptors of Partisans by Sample**

| **Descriptors Used by Democrats** | **Descriptors of Democrats** | | **Descriptors of Republicans** | |
| --- | --- | --- | --- | --- |
| **2016 Sample** | **2021 Sample** | **2016 Sample** | **2021 Sample** |
| **Most frequent response (%)** | <Non-Response>  (47.8%) | <Non-Response>  (25.9%) | <Non-Response>  (47.5%) | <Non-Response>  (28.2%) |
| **2nd** | Liberal  (35.4%) | Liberal  (19.1%) | Conservative  (29.1%) | Conservative  (13.2%) |
| **3rd** | Caring  (13.0%) | Caring  (18.1%) | Rich  (22.6%) | Ignorant  (12.0%) |
| **4th** | Open-Minded  (13.0%) | Smart  (12.8%) | White  (14.3%) | Prejudiced  (10.8%) |
| **5th** | Smart  (6.7%) | Open-Minded  (10.0%) | Prejudiced  (13.9%) | Self-Interested  (10.7%) |
| **6th** | Equality  (6.5%) | Good  (9.3%) | Ignorant  (9.4%) | Rich  (9.0%) |
| **7th** | Educated  (6.5%) | Friendly  (7.8%) | Closed-Minded  (7.2%) | Mean  (7.4%) |
| **8th** | Minorities  (4.9%) | Honest  (6.4%) | Self-Interested  (7.0%) | Dishonest  (6.8%) |
| **9th** | Youth  (4.3%) | Equality  (5.3%) | Senior-Citizens  (5.6%) | Good  (5.3%) |
| **10th** | Middle-Class  (4.3%) | Educated  (4.6%) | Religious  (5.6%) | Bad  (4.5%) |
| **Mean Positivity**  **(95% Conf Int)** | 5.59  (5.45, 5.73) | 5.90  (5.79, 6.00) | 3.46  (3.28, 3.64) | 3.55  (3.39, 3.72) |

**Table A2. Democrats’ Most Frequent Descriptors of Partisans by Sample**

| **Descriptors Used by Republicans** | **Descriptors of Democrats** | | **Descriptors of Republicans** | |
| --- | --- | --- | --- | --- |
| **2016 Sample** | **2021 Sample** | **2016 Sample** | **2021 Sample** |
| **Most frequent response (%)** | <Non-Response>  (47.9%) | Liberal  (28.0%) | <Non-Response>  (46.8%) | Conservative  (22.8%) |
| **2nd** | Liberal  (37.5%) | <Non-Response>  (18.9%) | Conservative  (38.0%) | <Non-Response>  (17.9%) |
| **3rd** | Ignorant  (10.5%) | Ignorant  (16.6%) | Rich  (10.2%) | Smart  (17.9%) |
| **4th** | Poor  (6.9%) | Socialists  (8.5%) | Smart  (7.4%) | Patriotism  (12.6%) |
| **5th** | Lazy  (6.6%) | Dishonest  (8.0%) | Religious  (6.6%) | Caring  (10.1%) |
| **6th** | Dishonest  (6.1%) | Mean  (6.4%) | White  (6.1%) | Honest  (9.7%) |
| **7th** | Socialists  (5.2%) | Self-Interested  (6.2%) | Honest  (6.1%) | Rich  (7.6%) |
| **8th** | Minorities  (5.0%) | Unrealistic  (5.5%) | Educated  (6.1%) | Good  (6.0%) |
| **9th** | Unrealistic  (4.1%) | Lazy  (4.8%) | Patriotism  (5.0%) | Strong  (5.7%) |
| **10th** | Youth  (3.6%) | Rich  (3.9%) | Individualist  (4.4%) | American  (5.5%) |
| **Mean Positivity**  **(95% Conf Int)** | 3.40  (3.20, 3.61) | 2.98  (2.78, 3.18) | 5.46  (5.30, 5.62) | 5.96  (5.82, 6.09) |

**Table A3. Republicans’ Most Frequent Descriptors of Partisans by Sample**

Note that the percentages in these tables occur at the *word level* and not at the respondent level. This means, for example, that a respondent who skips all four boxes is counted four times in the non-response category. When we consider the respondent level, about 65% of respondents provided at least one word for every box they were provided, about 4% left one box blank, about 5% left two boxed blank, 7 percent left three blank, and 18 percent left all four blank.

We next examine descriptors that are used more frequently in one of the two samples. Lijffijt et al. (2016) argue that when comparing the frequency in words across conditions, the set of words within a document should not be seen as independent. Thus, instead of comparing the frequency of each descriptor as a proportion of total words, we compare the proportion of participants in each sample who employ the descriptor.

Table A4 and A5 show the descriptors of Democrats and Republicans that were used statistically significantly more often in one of the two samples (*α* = .05) for the full sample or one of the partisan subsamples sorted by the overall frequency of the descriptor. In general, we see an increase in personal-trait words (e.g caring, smart, ignorant) and a decrease in words describing groups (e.g. poor, youth, minorities for Democrats, rich, white, senior citizens for Democrats) and issues (e.g. abortion).

|  | All | | | Dems Only | | | Reps Only | | |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Descriptor | 2016 | 2021 | *p* | 2016 | 2021 | *p* | 2016 | 2021 | *p* |
| liberal | 0.338 | 0.224 | **0.000** | 0.354 | 0.191 | **0.000** | 0.375 | 0.280 | **0.006** |
| caring | 0.070 | 0.110 | **0.001** | 0.130 | 0.181 | **0.027** | 0.011 | 0.034 | 0.053 |
| smart | 0.035 | 0.079 | **0.000** | 0.067 | 0.128 | **0.001** | 0.003 | 0.023 | **0.033** |
| ignorant | 0.046 | 0.069 | **0.021** | 0.009 | 0.007 | 0.970 | 0.105 | 0.166 | **0.017** |
| poor | 0.058 | 0.029 | **0.001** | 0.040 | 0.019 | 0.053 | 0.069 | 0.037 | **0.060** |
| good | 0.008 | 0.055 | **0.000** | 0.013 | 0.093 | **0.000** | 0.000 | 0.023 | **0.010** |
| friendly | 0.008 | 0.050 | **0.000** | 0.011 | 0.078 | **0.000** | 0.000 | 0.018 | **0.025** |
| honest | 0.011 | 0.039 | **0.000** | 0.025 | 0.064 | **0.004** | 0.000 | 0.005 | 0.560 |
| youth | 0.039 | 0.015 | **0.000** | 0.043 | 0.006 | **0.000** | 0.036 | 0.021 | 0.279 |
| minorities | 0.047 | 0.008 | **0.000** | 0.049 | 0.006 | **0.000** | 0.050 | 0.005 | **0.000** |
| rich | 0.011 | 0.025 | **0.024** | 0.007 | 0.010 | 0.830 | 0.011 | 0.039 | **0.025** |
| self interested | 0.009 | 0.024 | **0.010** | 0.000 | 0.004 | 0.441 | 0.019 | 0.062 | **0.005** |
| biden | 0.001 | 0.028 | **0.000** | 0.002 | 0.042 | **0.000** | 0.000 | 0.014 | 0.067 |
| mean | 0.002 | 0.026 | **0.000** | 0.000 | 0.004 | 0.441 | 0.006 | 0.064 | **0.000** |
| abortion | 0.025 | 0.010 | **0.004** | 0.022 | 0.007 | 0.045 | 0.028 | 0.016 | 0.384 |
| great | 0.000 | 0.025 | **0.000** | 0.000 | 0.046 | **0.000** | 0.000 | 0.002 | 1.000 |
| middle class | 0.023 | 0.008 | **0.002** | 0.043 | 0.010 | **0.000** | 0.006 | 0.005 | 1.000 |
| unions | 0.026 | 0.004 | **0.000** | 0.018 | 0.004 | **0.040** | 0.033 | 0.005 | 0.005 |
| cool | 0.001 | 0.021 | **0.000** | 0.000 | 0.036 | **0.000** | 0.000 | 0.002 | 1.000 |
| blue collar | 0.021 | 0.006 | **0.002** | 0.020 | 0.010 | 0.219 | 0.028 | 0.005 | **0.018** |
| supportive | 0.005 | 0.015 | **0.032** | 0.009 | 0.021 | 0.187 | 0.003 | 0.002 | 1.000 |
| women | 0.017 | 0.005 | **0.005** | 0.029 | 0.001 | **0.000** | 0.006 | 0.007 | 1.000 |
| happy | 0.004 | 0.013 | **0.040** | 0.009 | 0.019 | 0.243 | 0.000 | 0.009 | 0.184 |
| responsible | 0.003 | 0.013 | **0.018** | 0.004 | 0.025 | **0.017** | 0.000 | 0.000 | NA |
| radical | 0.002 | 0.013 | **0.007** | 0.000 | 0.003 | 0.699 | 0.003 | 0.023 | **0.033** |
| idiots | 0.005 | 0.011 | 0.180 | 0.000 | 0.003 | 0.699 | 0.006 | 0.028 | **0.036** |
| trustworthy | 0.001 | 0.013 | **0.003** | 0.002 | 0.025 | **0.006** | 0.000 | 0.000 | NA |
| crazy | 0.001 | 0.012 | **0.004** | 0.000 | 0.004 | 0.441 | 0.000 | 0.028 | **0.004** |
| patriotism | 0.002 | 0.010 | **0.042** | 0.004 | 0.017 | 0.114 | 0.000 | 0.000 | NA |
| sheep | 0.002 | 0.009 | 0.059 | 0.000 | 0.000 | NA | 0.003 | 0.025 | **0.021** |
| awesome | 0.000 | 0.010 | **0.003** | 0.000 | 0.019 | **0.007** | 0.000 | 0.002 | 1.000 |
| urban | 0.010 | 0.002 | **0.016** | 0.009 | 0.000 | **0.043** | 0.008 | 0.002 | 0.493 |

**Table A4. Descriptors of Democrats Significantly Different Between Samples**

|  | All | | | Dem Only | | | Rep Only | | |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Descriptor | 2016 | 2021 | *p* | 2016 | 2021 | *p* | 2016 | 2021 | *p* |
| conservative | 0.304 | 0.171 | **0.000** | 0.291 | 0.132 | **0.000** | 0.380 | 0.228 | **0.000** |
| rich | 0.165 | 0.087 | **0.000** | 0.226 | 0.090 | **0.000** | 0.102 | 0.076 | 0.242 |
| white | 0.102 | 0.039 | **0.000** | 0.143 | 0.042 | **0.000** | 0.061 | 0.034 | 0.114 |
| ignorant | 0.049 | 0.074 | **0.016** | 0.094 | 0.120 | 0.210 | 0.006 | 0.009 | 0.850 |
| smart | 0.034 | 0.076 | **0.000** | 0.004 | 0.018 | 0.083 | 0.074 | 0.179 | **0.000** |
| self interested | 0.035 | 0.068 | **0.001** | 0.070 | 0.107 | **0.041** | 0.003 | 0.011 | 0.312 |
| mean | 0.021 | 0.052 | **0.000** | 0.040 | 0.074 | **0.029** | 0.003 | 0.009 | 0.485 |
| senior citizens | 0.051 | 0.028 | **0.004** | 0.056 | 0.015 | **0.000** | 0.041 | 0.025 | 0.284 |
| patriotism | 0.021 | 0.048 | **0.001** | 0.000 | 0.010 | 0.089 | 0.050 | 0.126 | **0.000** |
| religious | 0.058 | 0.022 | **0.000** | 0.056 | 0.019 | **0.001** | 0.066 | 0.018 | **0.001** |
| good | 0.006 | 0.050 | **0.000** | 0.000 | 0.053 | **0.000** | 0.014 | 0.060 | **0.002** |
| caring | 0.011 | 0.041 | **0.000** | 0.002 | 0.010 | 0.254 | 0.028 | 0.101 | **0.000** |
| dishonest | 0.010 | 0.040 | **0.000** | 0.016 | 0.068 | **0.000** | 0.003 | 0.007 | 0.748 |
| trump | 0.006 | 0.036 | **0.000** | 0.011 | 0.040 | **0.007** | 0.000 | 0.028 | **0.004** |
| closed minded | 0.036 | 0.015 | **0.001** | 0.072 | 0.026 | **0.000** | 0.006 | 0.000 | 0.401 |
| hardworking | 0.012 | 0.025 | **0.039** | 0.002 | 0.008 | 0.357 | 0.030 | 0.053 | 0.163 |
| angry | 0.010 | 0.022 | **0.039** | 0.018 | 0.036 | 0.106 | 0.000 | 0.009 | 0.184 |
| loyal | 0.004 | 0.023 | **0.000** | 0.002 | 0.011 | 0.180 | 0.008 | 0.051 | **0.001** |
| friendly | 0.004 | 0.023 | **0.000** | 0.000 | 0.019 | **0.007** | 0.006 | 0.030 | **0.024** |
| abortion | 0.025 | 0.008 | **0.001** | 0.022 | 0.007 | **0.045** | 0.030 | 0.009 | 0.054 |
| bad | 0.002 | 0.023 | **0.000** | 0.002 | 0.045 | **0.000** | 0.003 | 0.000 | 0.928 |
| american | 0.004 | 0.022 | **0.001** | 0.002 | 0.006 | 0.703 | 0.008 | 0.055 | **0.001** |
| men | 0.019 | 0.008 | **0.029** | 0.031 | 0.006 | **0.001** | 0.008 | 0.011 | 0.921 |
| great | 0.001 | 0.020 | **0.000** | 0.000 | 0.017 | **0.015** | 0.003 | 0.032 | **0.005** |
| freedom | 0.006 | 0.016 | **0.046** | 0.000 | 0.006 | 0.288 | 0.017 | 0.039 | 0.092 |
| equality | 0.005 | 0.016 | **0.024** | 0.002 | 0.004 | 0.974 | 0.011 | 0.044 | **0.011** |
| economy | 0.016 | 0.007 | **0.046** | 0.004 | 0.003 | 1.000 | 0.036 | 0.011 | **0.039** |
| rural | 0.012 | 0.006 | 0.120 | 0.018 | 0.001 | **0.005** | 0.006 | 0.011 | 0.602 |
| trustworthy | 0.001 | 0.012 | **0.004** | 0.000 | 0.004 | 0.441 | 0.003 | 0.030 | **0.008** |
| cool | 0.001 | 0.012 | **0.004** | 0.000 | 0.019 | **0.007** | 0.000 | 0.005 | 0.560 |
| business | 0.015 | 0.003 | **0.001** | 0.007 | 0.004 | 0.864 | 0.025 | 0.000 | **0.003** |
| middle class | 0.012 | 0.004 | **0.042** | 0.000 | 0.000 | NA | 0.030 | 0.005 | **0.010** |
| awesome | 0.000 | 0.012 | **0.002** | 0.000 | 0.008 | 0.130 | 0.000 | 0.023 | **0.010** |
| immoral | 0.000 | 0.011 | **0.002** | 0.000 | 0.019 | **0.007** | 0.000 | 0.000 | NA |
| wrong | 0.001 | 0.010 | **0.016** | 0.002 | 0.014 | 0.091 | 0.000 | 0.000 | NA |
| boring | 0.000 | 0.010 | **0.005** | 0.000 | 0.013 | **0.043** | 0.000 | 0.002 | 1.000 |
| like | 0.000 | 0.008 | **0.010** | 0.000 | 0.010 | 0.089 | 0.000 | 0.011 | 0.110 |
| irresponsible | 0.001 | 0.008 | **0.048** | 0.000 | 0.013 | **0.043** | 0.000 | 0.002 | 1.000 |
| fun | 0.001 | 0.008 | **0.048** | 0.000 | 0.004 | 0.441 | 0.003 | 0.011 | 0.312 |
| supportive | 0.000 | 0.008 | **0.015** | 0.000 | 0.006 | 0.288 | 0.000 | 0.007 | 0.315 |
| brave | 0.000 | 0.008 | **0.015** | 0.000 | 0.004 | 0.441 | 0.000 | 0.018 | **0.025** |

**Table A5. Descriptors of Republicans Significantly Different Between Samples**

*A.2 Analysis of Stereotype Content Using Hand-Coding*

As a confirmation of these analyses, we conducted an inductive coding of the descriptors listed by respondents. A research assistant unaware of the other results from this paper generated a list of six categories of descriptors: Personal Traits, Ideological Labels, Demographic Groups, Values, Issues, and Symbols and Party Leaders, and then applied these to all descriptors used by at least three respondents. A second coder, one of the authors of this study, double-coded 59 randomly selected descriptors, which produced agreement on 54 of 59 descriptors for a Krippendorff’s alpha (nominal) of .86. We apply these codes to respondents’ descriptors from the two years and for each category compare the proportion who use at least one descriptor from that category. Tables A6 and A7 show the results overall, and within each partisan sub-group. In line with the STM results presented in the main text, the proportion of respondents listing at least one personal trait increased for descriptors of each party and for each partisan subsample of respondents. In most of these analyses, the proportion using ideological labels, demographic groups, and issues decrease, the exception being no statistically significant change in Republicans’ use of ideological labels and demographic groups to describe Democrats or in Democrats’ use of issues to describe themselves.

|  | All | | | Dems Only | | | Reps Only | | |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Category | 2016 | 2021 | *p* | 2016 | 2021 | *p* | 2016 | 2021 | *p* |
| Personal Traits | 0.412 | 0.673 | **0.00** | 0.439 | 0.677 | **0.00** | 0.449 | 0.703 | **0.00** |
| Ideology | 0.352 | 0.263 | **0.00** | 0.361 | 0.217 | **0.00** | 0.397 | 0.343 | 0.13 |
| Demo Groups | 0.239 | 0.143 | **0.00** | 0.287 | 0.129 | **0.00** | 0.190 | 0.145 | 0.11 |
| Values | 0.071 | 0.083 | 0.29 | 0.117 | 0.114 | 0.97 | 0.025 | 0.39 | 0.35 |
| Issues | 0.109 | 0.071 | **0.00** | 0.092 | 0.063 | 0.08 | 0.138 | 0.080 | **0.01** |
| Symbols/Leaders | 0.01 | 0.02 | 0.10 | 0.020 | 0.025 | 0.74 | 0.008 | 0.014 | 0.67 |

**Table A6. Respondents Describing Democrats with One or More of the Category’s Descriptors**

|  | All | | | Dems Only | | | Reps Only | | |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Category | 2016 | 2021 | *p* | 2016 | 2021 | *p* | 2016 | 2021 | *p* |
| Personal Traits | 0.397 | 0.671 | **0.00** | 0.464 | 0.663 | **0.00** | 0.377 | 0.731 | **0.00** |
| Ideology | 0.321 | 0.207 | **0.00** | 0.305 | 0.163 | **0.00** | 0.399 | 0.267 | **0.00** |
| Demo Groups | 0.346 | 0.212 | **0.00** | 0.386 | 0.171 | **0.00** | 0.333 | 0.255 | **0.02** |
| Values | 0.091 | 0.116 | 0.05 | 0.031 | 0.039 | 0.61 | 0.176 | 0.257 | **0.01** |
| Issues | 0.089 | 0.048 | **0.00** | 0.070 | 0.033 | **0.01** | 0.124 | 0.062 | **0.00** |
| Symbols/Leaders | 0.019 | 0.056 | **0.00** | 0.029 | 0.061 | **0.02** | 0.008 | 0.041 | **0.01** |

**Table A7. Respondents Describing Republicans with One or More of the Category’s Descriptors**

Finally, we evaluate the main finding that character-focused stereotypes of the two parties have become more common by assigning each respondent a “type” corresponding to the category of descriptor they used most frequently. Respondents who listed the same number of more than one category (e.g. two “Personal Traits” and two “Issues”) were categorized as both types. Respondents who listed no descriptors are listed as “NA.” Tables A8 and A9 show a similar result to the analysis in the main text. The proportion of respondents using primarily Personal Trait terms to describe partisans increases between the two samples, while the proportion using demographic groups decreases. The proportion using primarily ideological terms also decreases, though the difference is only statistically significant for descriptors of Republicans. The percent primarily using other terms changes little or is extremely small in both samples.

|  | All | | | Dems Only | | | Reps Only | | |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Category | 2016 | 2021 | *p* | 2016 | 2021 | *p* | 2016 | 2021 | *p* |
| Personal Traits | 0.356 | 0.627 | **0.00** | 0.368 | 0.640 | **0.00** | 0.388 | 0.653 | **0.00** |
| Ideology | 0.191 | 0.166 | 0.12 | 0.179 | 0.128 | **0.02** | 0.240 | 0.225 | 0.69 |
| Demo Groups | 0.160 | 0.084 | **0.00** | 0.182 | 0.071 | **0.00** | 0.129 | 0.101 | 0.25 |
| Values | 0.033 | 0.047 | 0.13 | 0.056 | 0.058 | 0.97 | 0.011 | 0.025 | 0.22 |
| Issues | 0.059 | 0.047 | 0.23 | 0.047 | 0.040 | 0.69 | 0.080 | 0.057 | 0.27 |
| Symbols/Leaders | 0.009 | 0.015 | 0.26 | 0.013 | 0.019 | 0.59 | 0.008 | 0.005 | 0.84 |
| NA | 0.411 | 0.187 | **0.00** | 0.383 | 0.211 | **0.00** | 0.380 | 0.110 | **0.00** |

**Table A8. Respondents’ Type for Descriptors of Democrats.**

Note: Rows add up to more than 1 because respondents could be categorized as more than one type

|  | All | | | Dems Only | | | Reps Only | | |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Category | 2016 | 2021 | *p* | 2016 | 2021 | *p* | 2016 | 2021 | *p* |
| Personal Traits | 0.335 | 0.629 | **0.00** | 0.395 | 0.630 | **0.00** | 0.317 | 0.676 | **0.00** |
| Ideology | 0.157 | 0.116 | **0.00** | 0.119 | 0.089 | 0.12 | 0.226 | 0.133 | **0.00** |
| Demo Groups | 0.245 | 0.129 | **0.00** | 0.240 | 0.106 | **0.00** | 0.264 | 0.159 | **0.00** |
| Values | 0.052 | 0.071 | 0.07 | 0.016 | 0.025 | 0.39 | 0.102 | 0.159 | **0.02** |
| Issues | 0.059 | 0.038 | **0.02** | 0.047 | 0.028 | 0.12 | 0.074 | 0.048 | 0.16 |
| Symbols/Leaders | 0.010 | 0.043 | **0.00** | 0.013 | 0.045 | **0.01** | 0.003 | 0.032 | **0.01** |
| NA | 0.405 | 0.186 | **0.00** | 0.390 | 0.225 | **0.00** | 0.366 | 0.092 | **0.00** |

**Table A9. Respondents’ Type for Descriptors of Republicans**

Note: Rows add up to more than 1 because respondents could be categorized as more than one type

**Appendix B: Comparison of Panels**

As noted in the main text, we considered carefully the reasons for the shift in the nonresponse and generic topics across years. Our primary concerns about this change were that (1) this change was the product of systematic differences between the panel in 2016 and the panel in 2021 and (2) these types of differences would influence or distort the changes in time presented in the main analyses. To evaluate these issues, we conducted a series of supplemental analyses in addition to the results presented in the article.

Regarding systematic differences between the two online panels, Table B1 gives the demographic breakdown of the sample in 2016 and the sample in 2021. This table indicates that there are some differences between the two surveys, although these differences tend to be relatively small. As noted in the discussion of the main analyses, we included all of the variables in Table B1 as covariates in our STM to account for the fact that these kinds of respondents might use topics in different amounts. The degree to which the surveys differ on these demographic variables, then, should not confound the results presented in the main text.

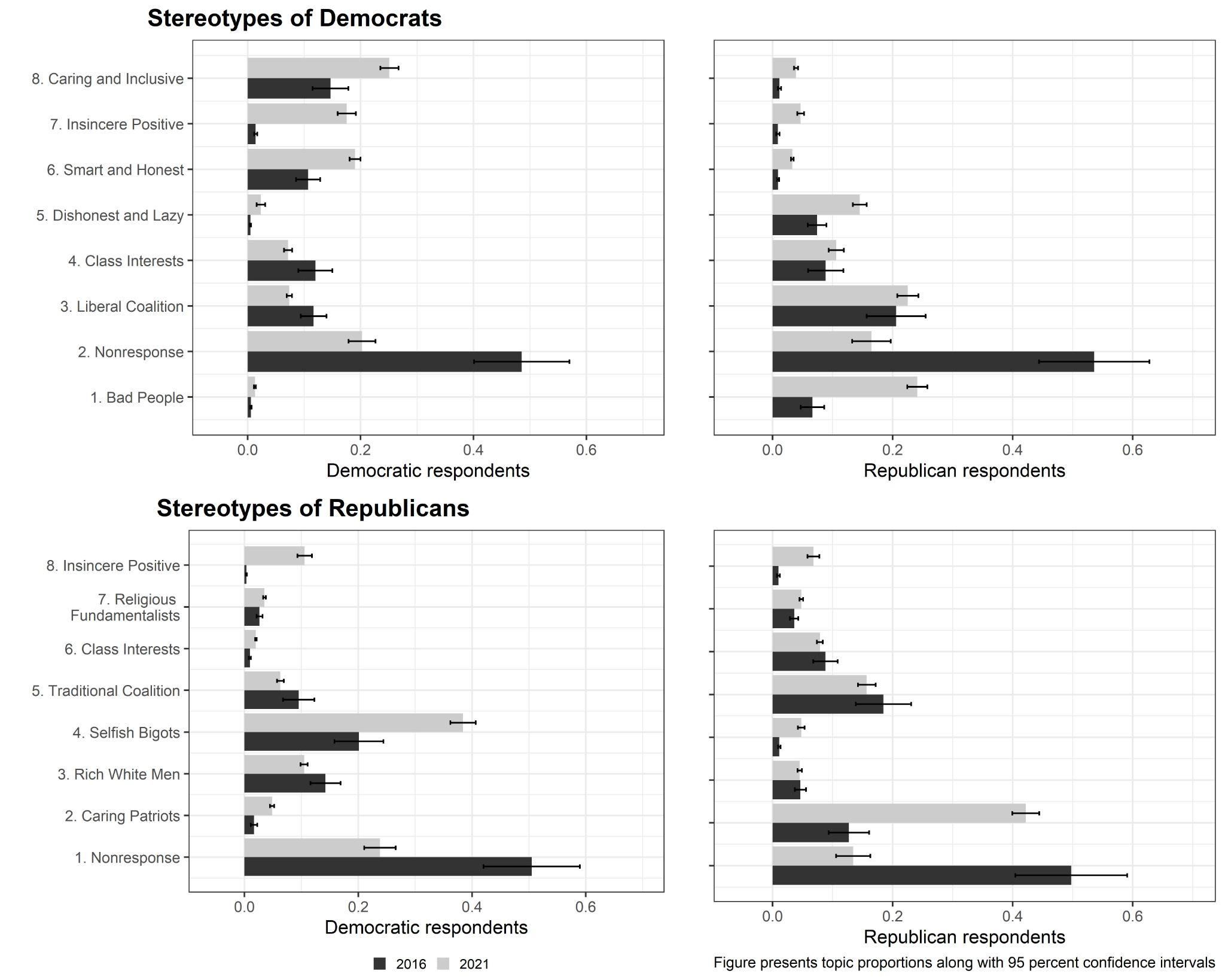
To further address this point, and as briefly noted in the main text, we considered alternative methods of estimating the changes in topic use across years that incorporate survey weights to weight the samples in both years to be more comparable to one another. To do this, we create sampling targets based on the U.S. Census’s 2017-2021 5 year population estimates from the American Community Survey. We create weights based off on benchmarks from the Census on age, income, education, race, ethnicity, and gender. These are implemented in R using the *anesrake* package, as shown in our replication files. We structured these weights such that no observation could receive a weight larger than 5 (which is the default for this package). We constructed these weights separately for the 2016 and 2021 surveys, as our objective was to reweight the surveys from both years so that they would be more comparable to *each other* rather than to produce a combined dataset that was more reflective of the American population. Examining the unweighted and weighted demographic characteristics of these surveys suggests that the samples are much more comparable to each other and dramatically closer to the Census benchmarks after weighting.

With these weights, we replicated the analysis behind Figure 1 in the main text in different ways. First, we calculated weighted and unweighted averages of the prevalence of each topic. These are presented in Figures B.1 and B.2, respectively. The main takeaway from these figures is that although there are some small differences between these graphs and Figure 1, the patterns, especially with respect to change over time, mirror those discussed in the main text. This is especially true of the weighted means, which is some evidence that the differences between years are not a product of the different compositions of the samples and data sources in 2016 and 2021. We also replicate these estimates using regressions that predict topic prevalence as a function of the covariates used in the STM procedures - these are shown in Figure B.3 and lead to the same conclusions as the other weighted and unweighted analyses.

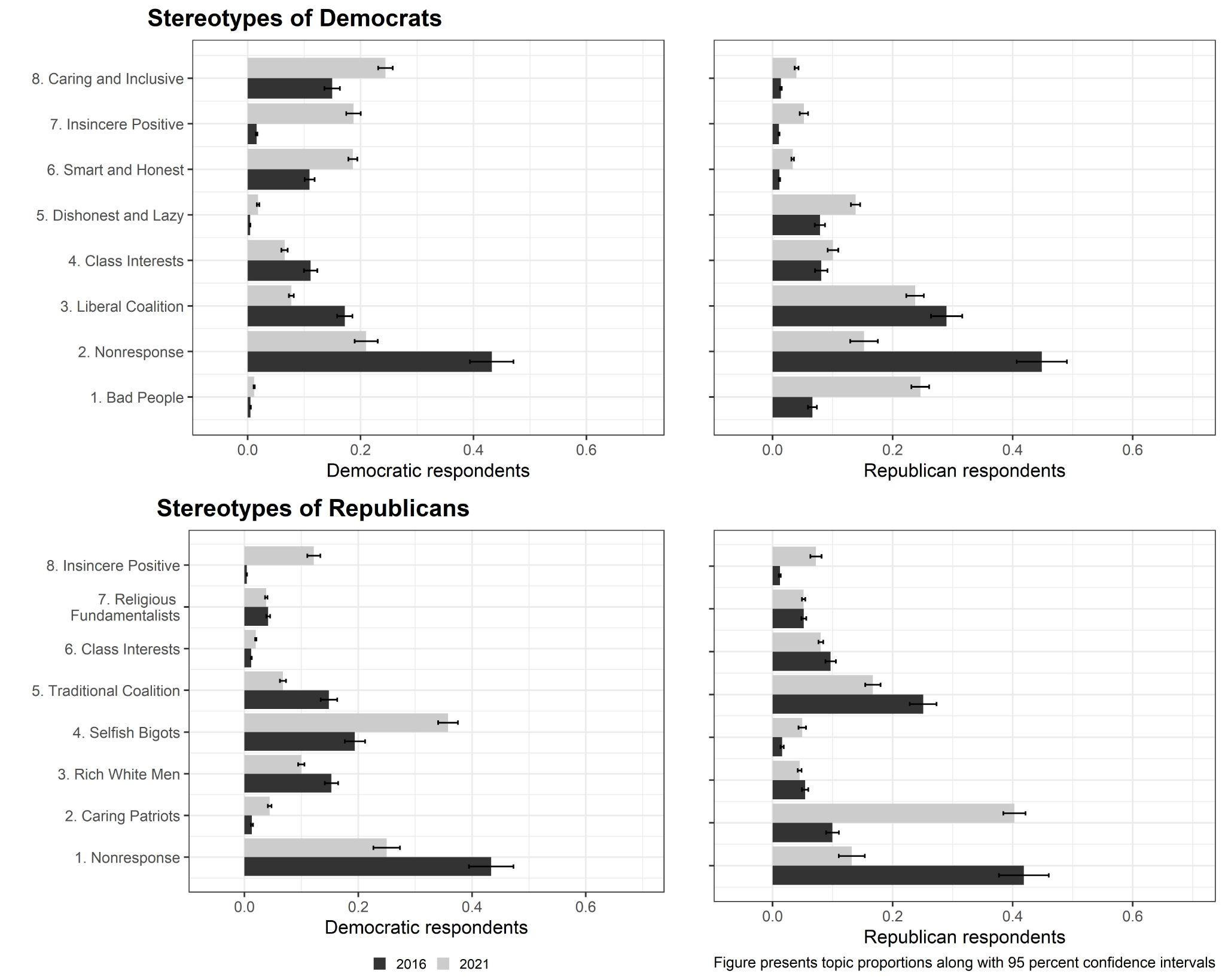
|  | **2016 Research Now sample** | **2021 Lucid sample** |
| --- | --- | --- |
| **Percent female** | 50.7 | 53.4 |
| **Percent Republican** | 37.0 | 30.0 |
| **Percent Democrat** | 45.5 | 49.5 |
| **Percent White** | 80.4 | 73.9 |
| **Percent Hispanic** | 8.0 | 11.1 |
| **Average age** | 43.6 | 45.5 |
| **Average income** | $75.000-$100,000 | $50,000-$75,000 |
| **Average education** | Bachelor’s degree | Associate’s degree |
| **Average political interest (1-7)[[1]](#footnote-0)** | 4.5 | 4.8 |
| **Average political knowledge (0-4)[[2]](#footnote-1)** | 2.5 | 2.0 |

**Table B1. Demographics across waves**

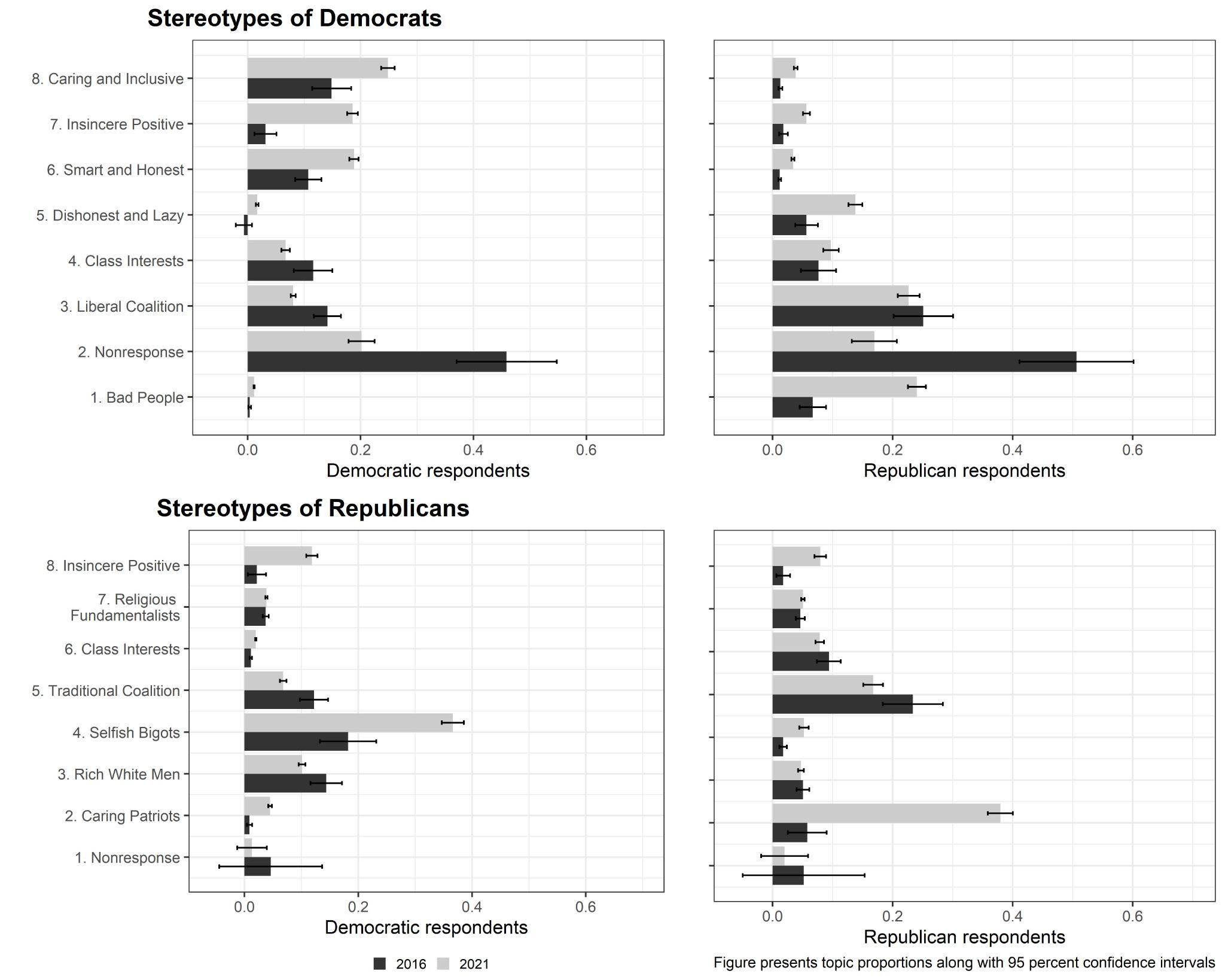
**Figure B.1: Weighted mean estimates of topic prevalence**

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**Figure B.2: Unweighted mean estimates of topic prevalence**

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**Figure B.3: Weighted regression predictions of topic prevalence**

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**Appendix C: Comparison of Panels Using Attention Check Items**

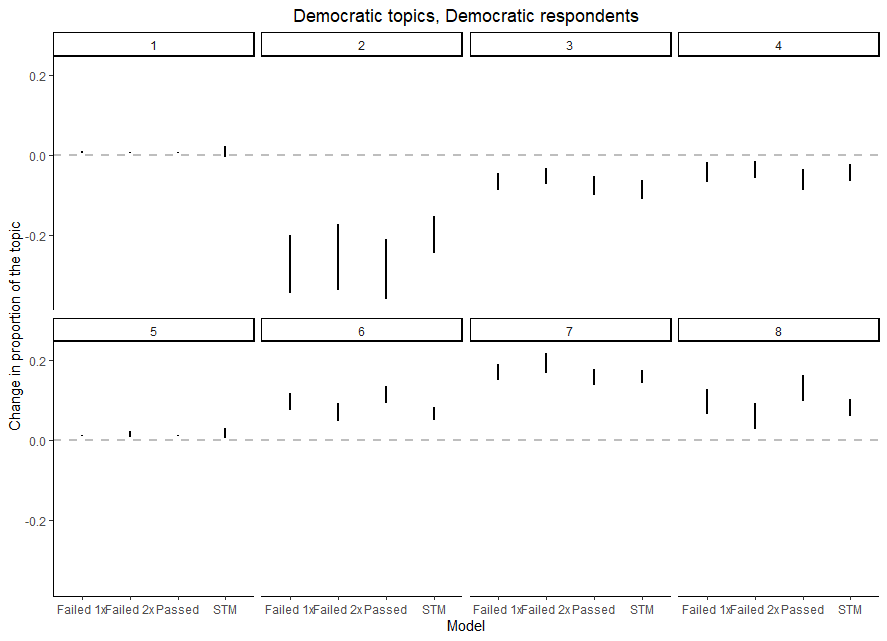
In a related way, we were also concerned that differences in attentiveness and survey quality might correlate with year, produce the shifts we see in the nonresponse topics, and confound the other differences in topic use by year. To evaluate this possibility, we considered our attention check item, which asked respondents to choose a specific answer combination to a question about media consumption (see Berinsky, Margolis, and Sances 2014). Respondents who chose the correct answer choice combination were allowed to proceed; those who did not were shown an error message and asked to complete the item again. At this point, respondents were allowed to proceed even if they failed a second time, creating an attention check variable with three values—passed on first attempt, failed once, and failed twice. Table C1 shows the distribution of attentiveness for both years on this variable.

|  | **2016 sample** | **2021 sample** |
| --- | --- | --- |
| **Passed on first attempt** | 312 (31.6%) | 441 (30.4%) |
| **Failed on first attempt** | 362 (36.6%) | 484 (33.3%) |
| **Failed both attempts** | 314 (31.8%) | 527 (36.3%) |
| **N** | 988 | 1452 |

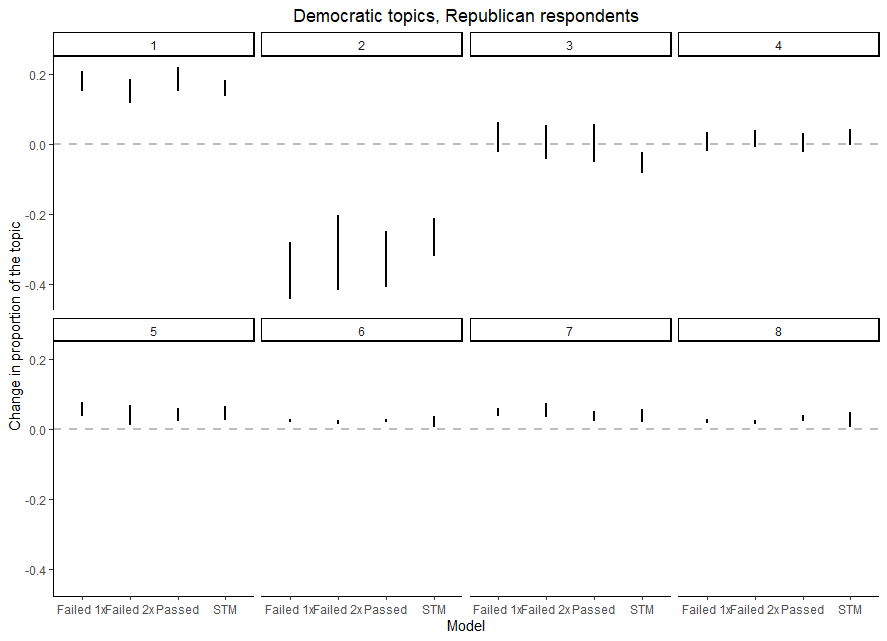
**Table C1. Attention check results by year**

A chi-squared test of the independence of these variables gives a p-value of 0.061, indicating some suggestive evidence that failing the attention check may be related to the year of survey. Transforming this to a binary variable where 1 is passing on the first attempt gives an insignificant difference between the years (p=0.556). This seems to suggest some small changes by year, although the general distribution seems quite similar.

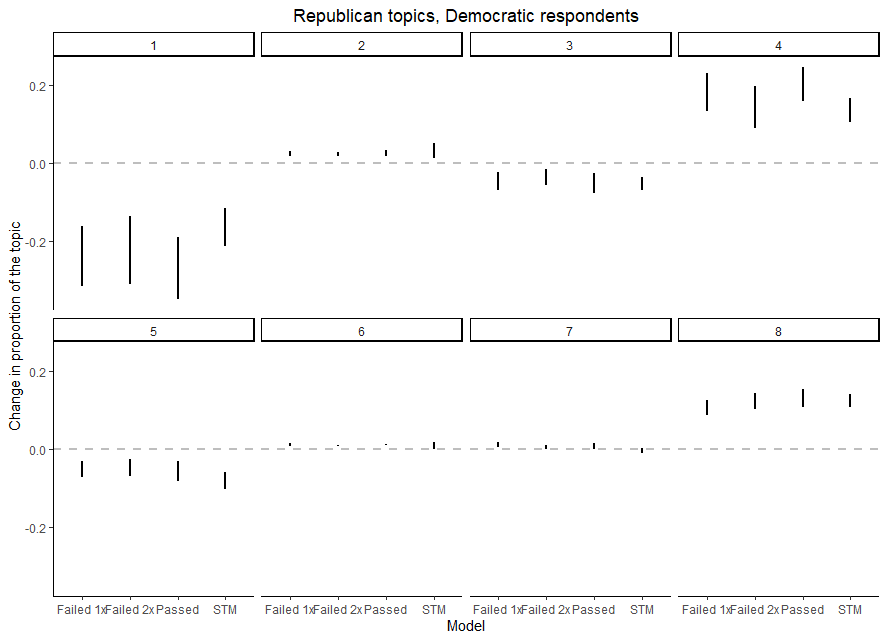
With this attention check variable, we next ran versions of the analyses in the main text separately for those who passed on the first attempt, failed once, and failed twice. In other words, we ran separate models for each topic for Democrats who passed the attention check, Democrats who failed once, Democrats who failed twice, Republicans who passed, Republicans who failed once, and Republicans who failed twice. Figures C1-C4 compare each version of the models to the original STM results. These figures indicate that there are only very small, if any, differences between the models using respondents with different levels of attention. This suggests to us that the shifts we observe in the topics across the survey years do not seem to be confounded with differences in attention/quality of responding.



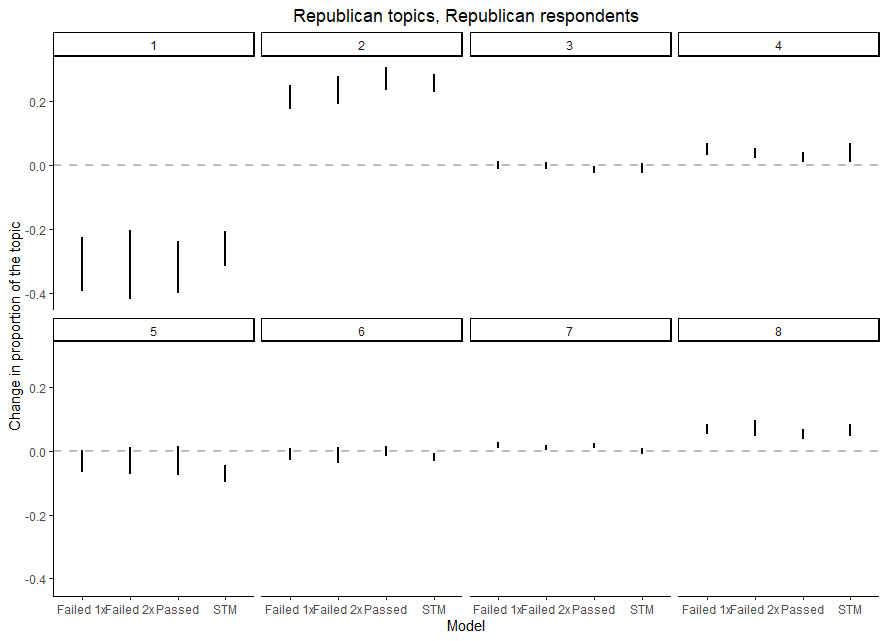
**Figure C1. Democratic topics, Democratic respondents, different levels of attentiveness**



**Figure C2. Democratic topics, Republican respondents, different levels of attentiveness**



**Figure C3. Republican topics, Democratic respondents, different levels of attentiveness**



**Figure C4. Republican topics, Republican respondents, different levels of attentiveness**

**Appendix D: Analysis of Other Prevalence Covariates and Alternative Displays of Main Results**

Given our focus on year and partisanship, we do not discuss the influence of the other covariates on topic use in the main article. Tables D1 and D2 present a summary of the relationship between the various topics and the other covariates we use in our STM approach. A positive sign indicates that the variable positively predicted that topic’s use in a statistically significant way (p<0.10), and a negative sign suggests a statistically significant, negative connection between the covariate and topic use.

|  | Topic 1 | Topic 2 | Topic 3 | Topic 4 | Topic 5 | Topic 6 | Topic 7 | Topic 8 |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Income |  | **-** |  | **-** |  | **+** | **+** |  |
| Gender | **-** |  | **+** | **+** | **+** | **+** |  | **-** |
| White |  | **+** | **-** | **-** | **+** | **+** | **+** | **+** |
| Interest | **-** | **+** | **-** |  | **-** |  | **-** | **+** |
| Education | **+** | **-** |  |  | **+** | **-** | **-** |  |
| Hispanic |  |  |  | **+** | **-** |  | **-** | **+** |
| Age | **-** | **+** | **+** |  | **+** | **+** |  | **-** |
| Political knowledge | **-** | **-** | **+** |  | **+** | **+** | **+** | **-** |

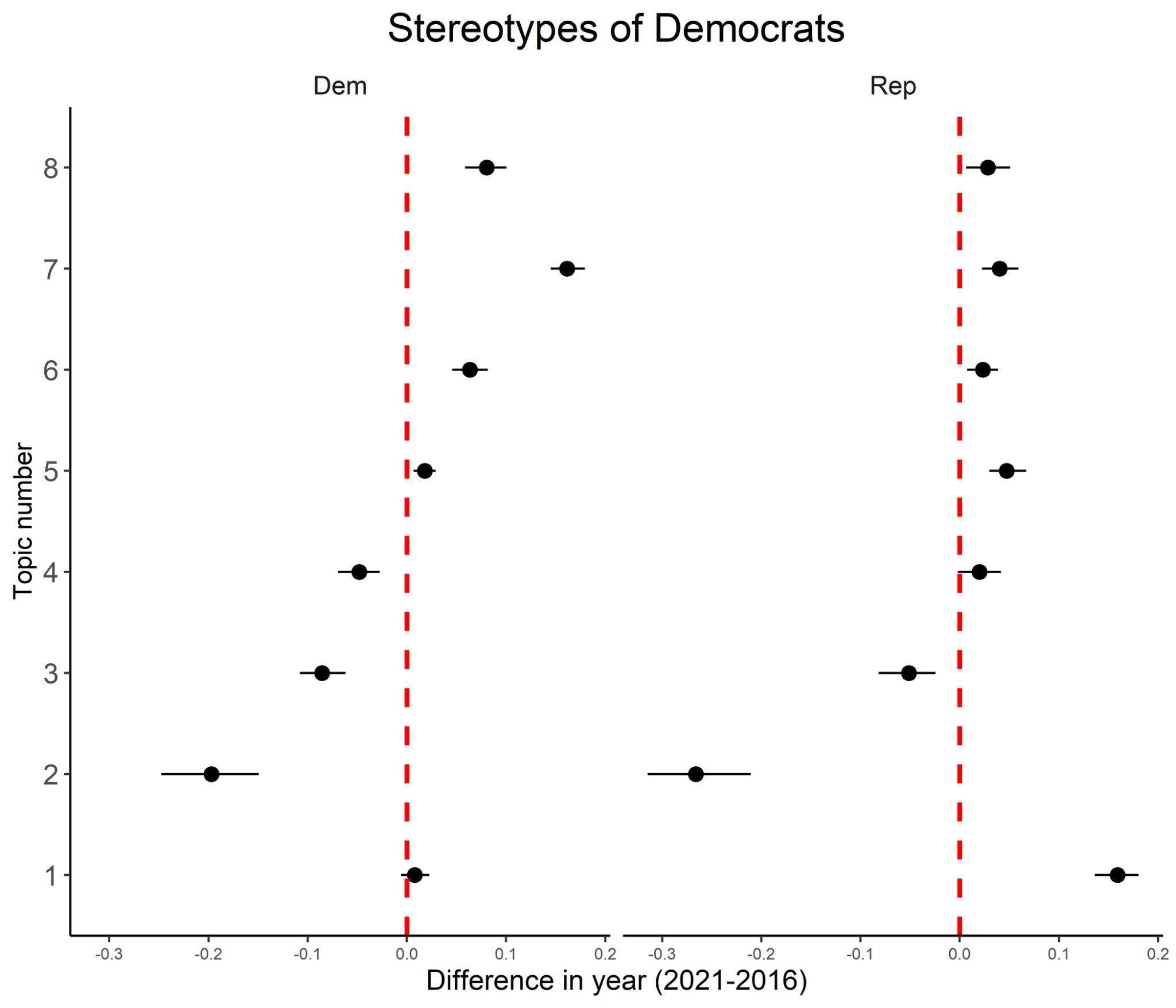
**Table D1. Predictors of Republican topics**

|  | Topic 1 | Topic 2 | Topic 3 | Topic 4 | Topic 5 | Topic 6 | Topic 7 | Topic 8 |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Income |  |  | **+** |  | **-** | **-** | **+** | **-** |
| Gender | **+** | **+** |  |  |  | **+** | **-** | **+** |
| White | **+** |  | **+** |  | **+** | **-** |  | **-** |
| Interest | **-** | **-** | **-** | **-** | **-** |  | **+** | **+** |
| Education | **-** | **-** | **+** |  | **-** |  |  |  |
| Hispanic |  |  |  |  |  |  | **+** |  |
| Age | **+** | **-** | **+** | **+** | **+** |  | **-** | **+** |
| Political knowledge |  | **-** | **+** | **+** | **-** | **+** | **-** | **+** |

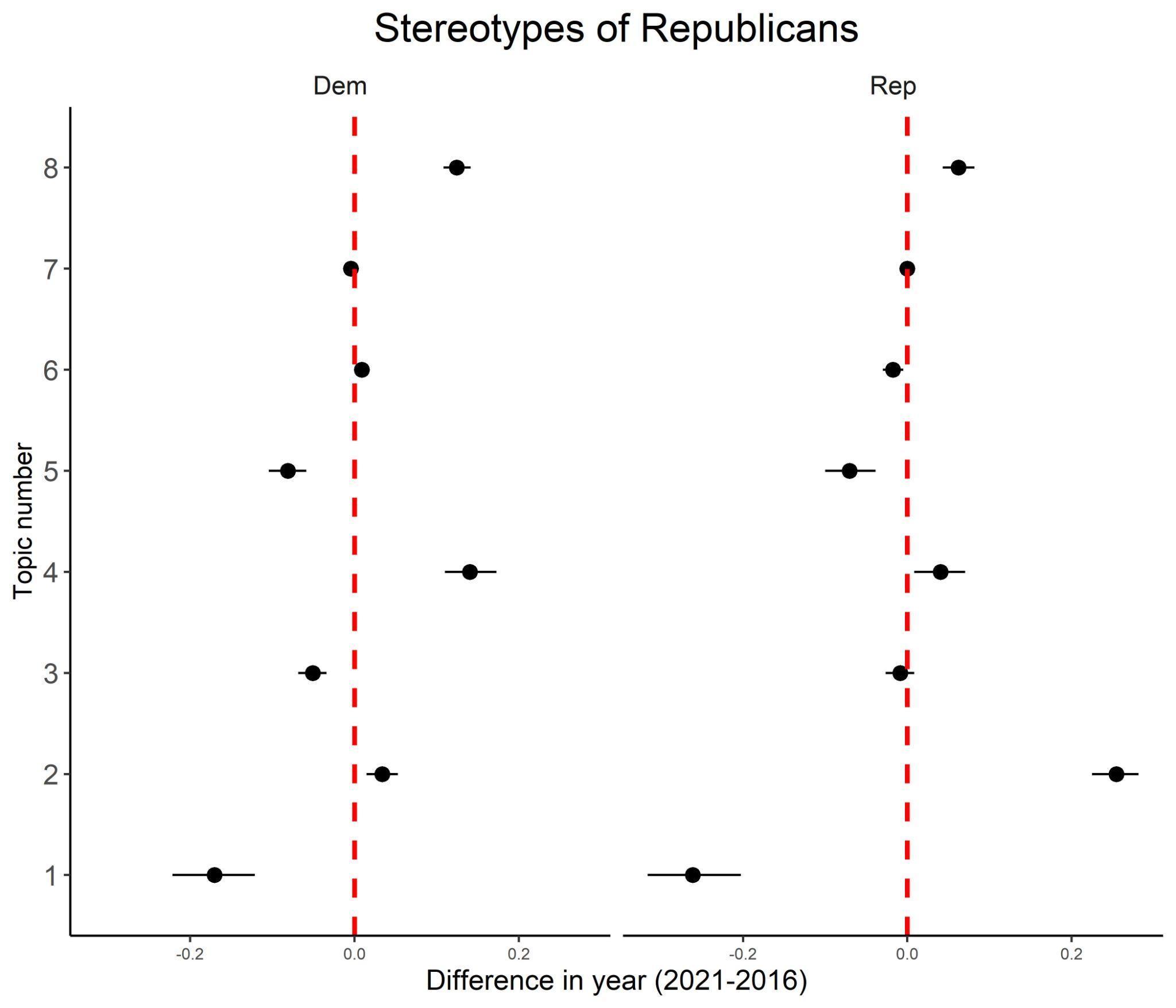
**Table D2. Predictors of Democratic topics**

**Appendix E: Alternative Displays of Main Results**

In the main text, Figure 1 presents the proportions of each topic used by Republicans and Democrats in each survey. Alternative versions of these figures are presented in figures E1 and E2 that directly show the shifts (rather than the underlying proportions). We ultimately prefer the version in Figure 1 as it provides additional information, but figures E1 and E2 focus more directly on *change* between the surveys. These figures are completely consistent with our discussion in text about changes over time.

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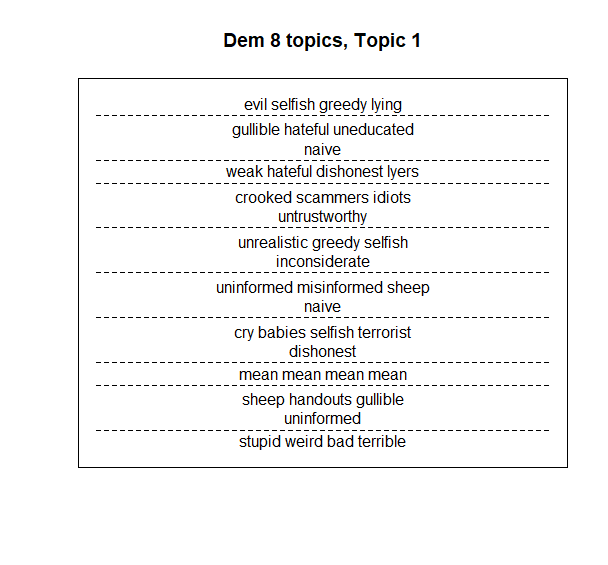
**Figure E1: Stereotypes of Democrats, changes over time**

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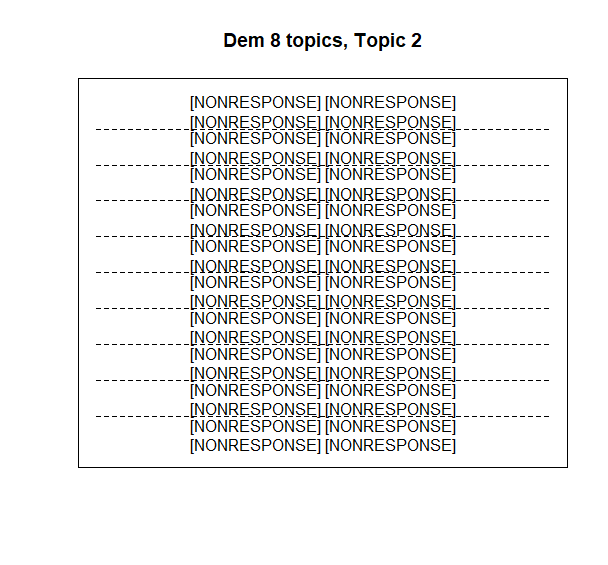
**Figure E2: Stereotypes of Republicans, changes over time**

**Appendix F: Exemplar Documents by Topic**

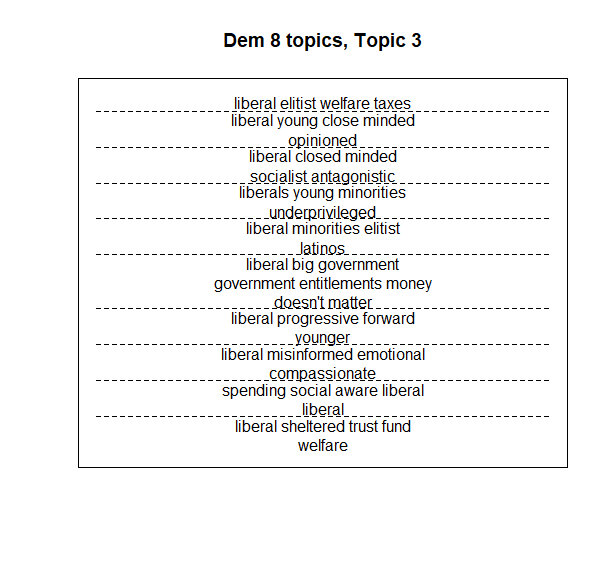
As noted in the text, one important part of the STM process is referring to documents high in a given topic to help determine what that topic’s meaning is. These documents are referred to as exemplar documents, and we considered ten such texts for each topic. The figures below present those exemplar texts for each of the topics we analyze.



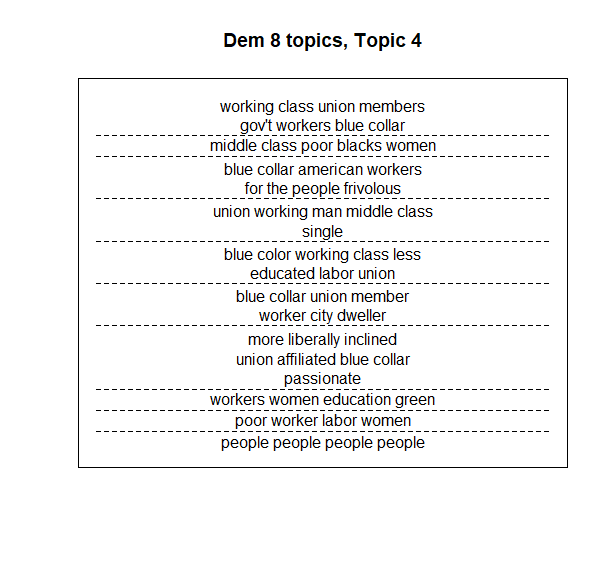
**Figure F1. Democratic topics exemplars, Topic 1**



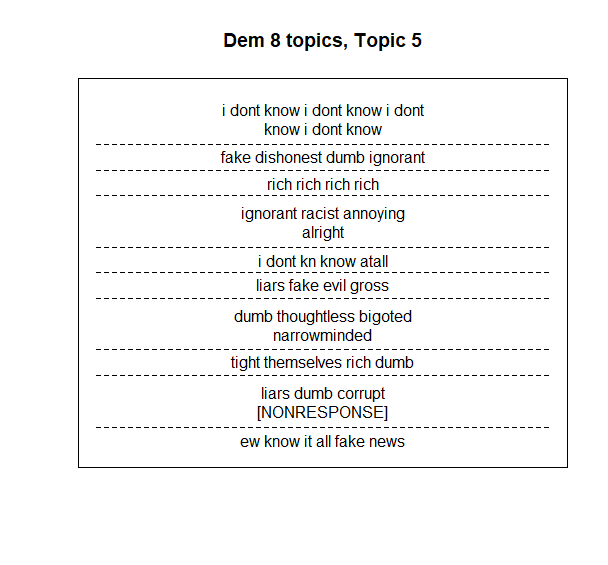
**Figure F2. Democratic topics exemplars, Topic 2**



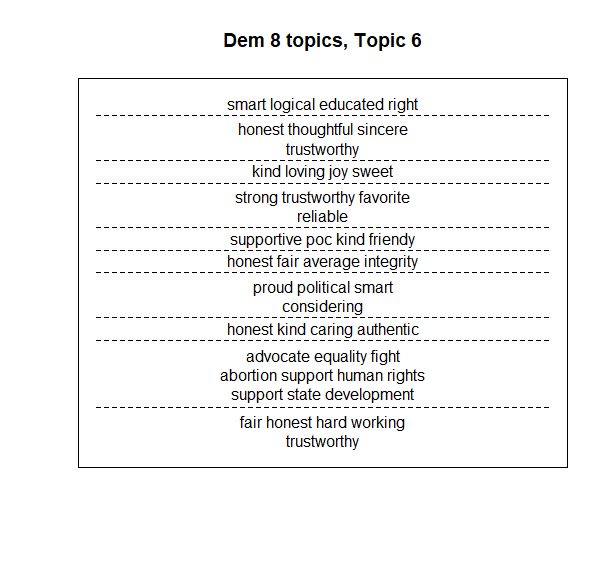
**Figure F3. Democratic topics exemplars, Topic 3**



**Figure F4. Democratic topics exemplars, Topic 4**



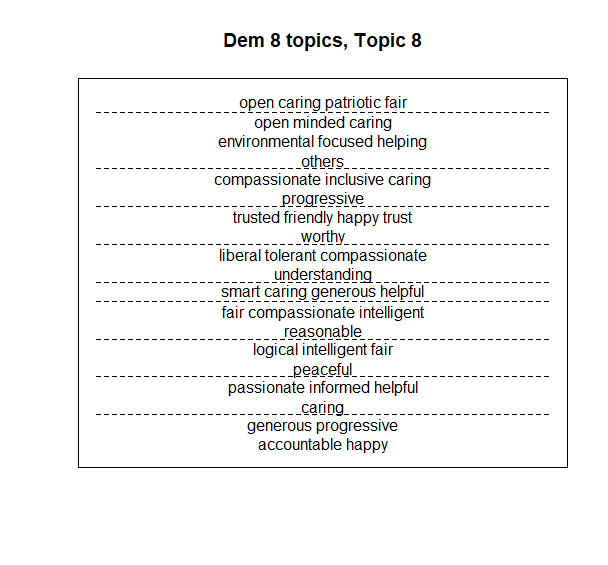
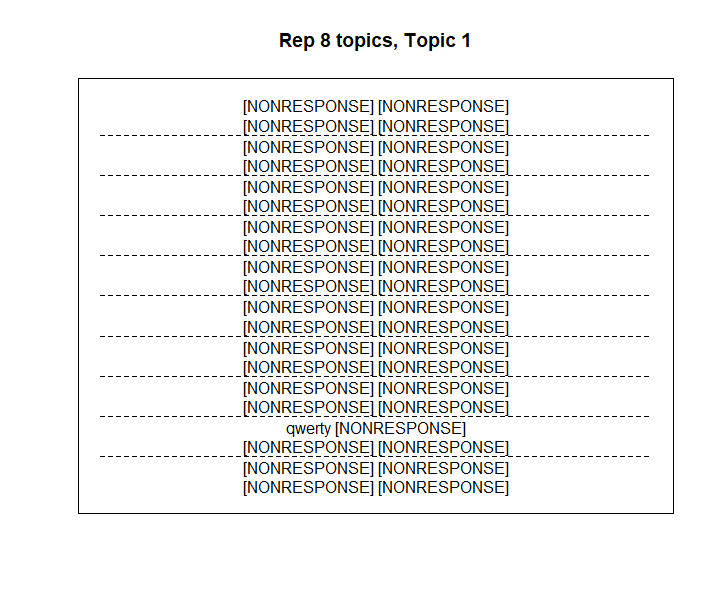
**Figure F5. Democratic topics exemplars, Topic 5**



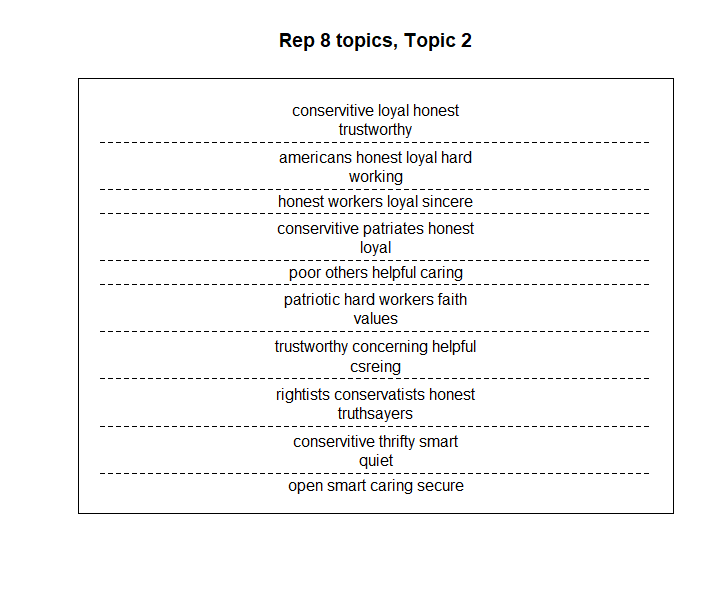
**Figure F6. Democratic topics exemplars, Topic 6**



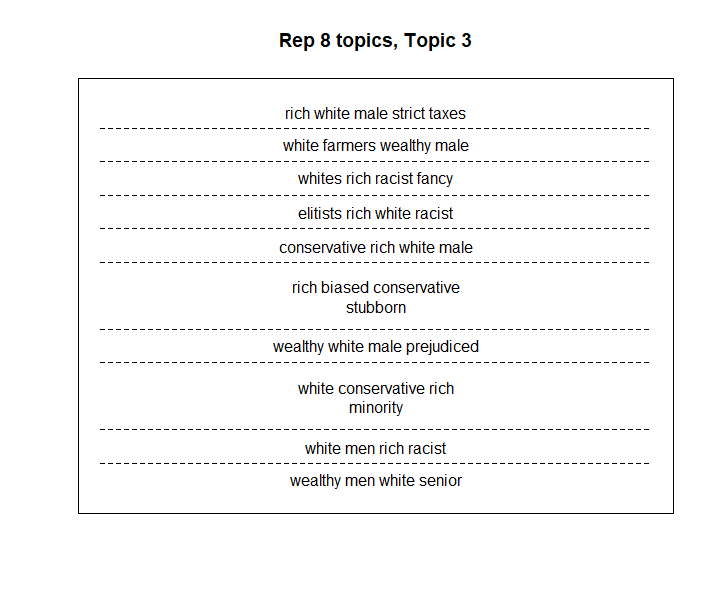
**Figure F7. Democratic topics exemplars, Topic 7**

**Figure F8. Democratic topics exemplars, Topic 8**

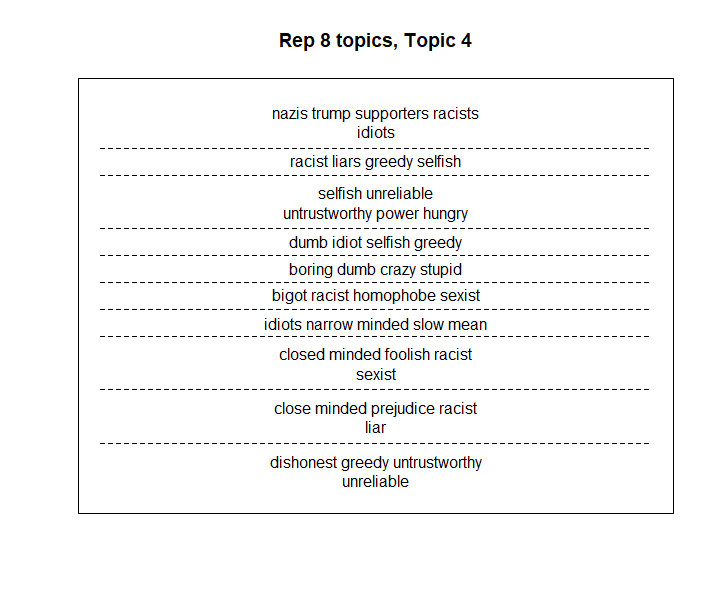
**Figure F9. Republican topics exemplars, Topic 1**

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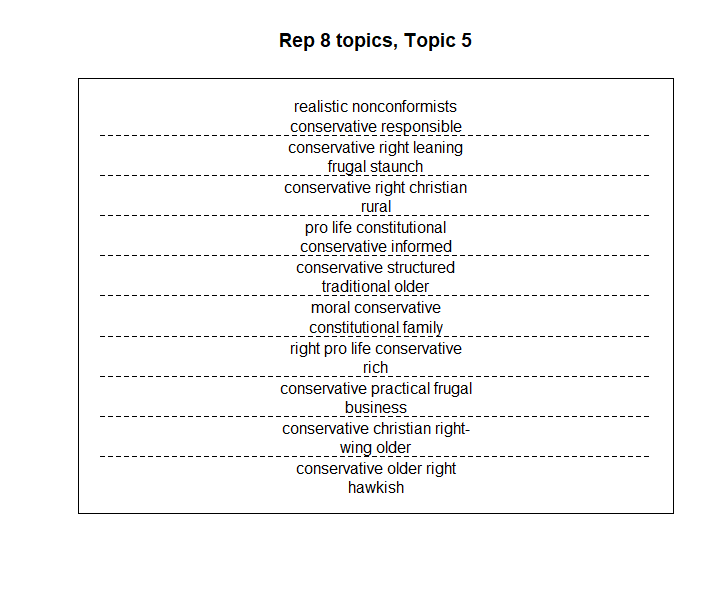
**Figure F10. Republican topics exemplars, Topic 2**

****

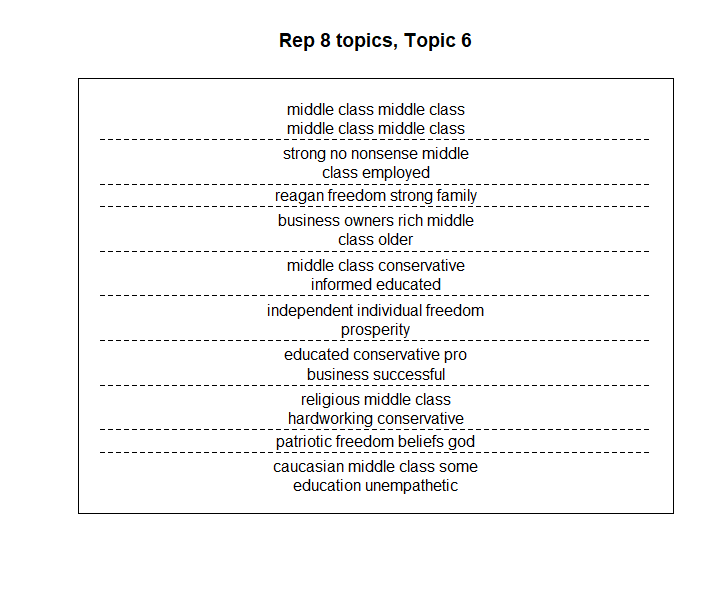
**Figure F11. Republican topics exemplars, Topic 3**

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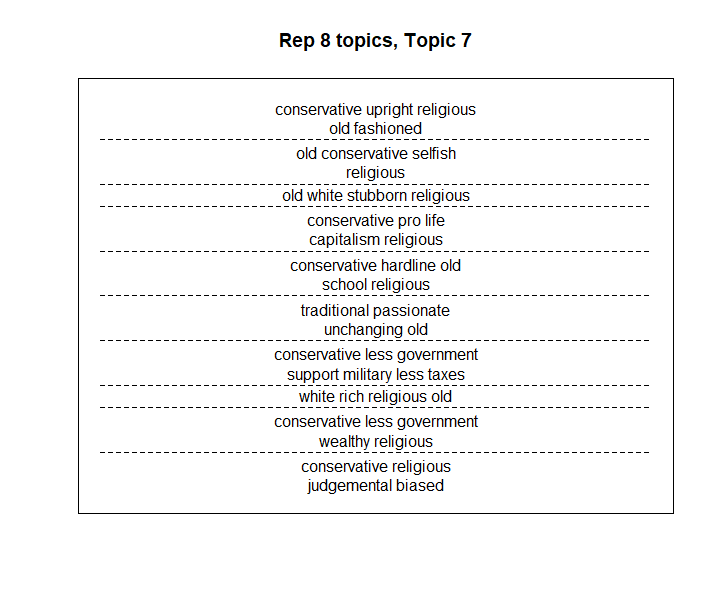
**Figure F12. Republican topics exemplars, Topic 4**

****

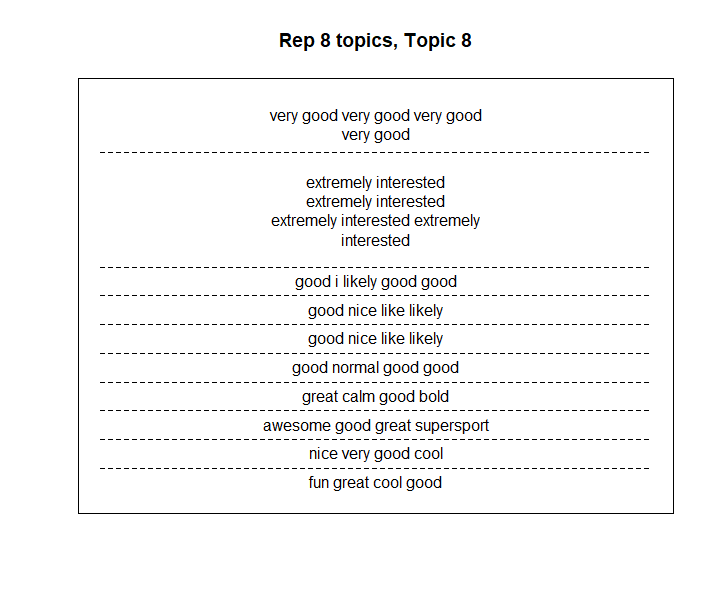
**Figure F13. Republican topics exemplars, Topic 5**

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**Figure F14. Republican topics exemplars, Topic 6**

****

**Figure F15. Republican topics exemplars, Topic 7**

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**Figure F16. Republican topics exemplars, Topic 8**

**Appendix G: Checking for Insincere Respondents**

Some researchers have noted an increase in what Kennedy et al. (2021) term “insincere” responses on representative non-probability panels like those we use to recruit responses. Troublingly, Kennedy et al. (2021)’s extensive study of these responses finds that standard closed-ended attention checks appear to do a poor job at detecting these responses. This type of low-quality responses are potentially problematic for structural topic models because such responses often include responses to open-ended questions that are not blank and not gibberish, but also not responsive to the question. For example, Kennedy et al. (2021) coded responses to a series of open-ended questions and found that between two and four percent of respondents from what they term “Opt-in panels'' gave multiple “non-sequitur” - that is, answers that were lexical but were not plausible answers to the question asked - answers to a series of open-ended questions. If the proportion of respondents giving this type of response changed from 2016 to 2021, then some of the change in topics that we interpret as change in stereotypes may in fact be an increase in these kinds of responses.

We investigated this possibility using an open-ended question that asked “Who is the current Secretary of State?” This was part of the political knowledge battery, which appeared after the stereotype questions in the survey.[[3]](#footnote-2) We identify insincere responses as Kennedy et al. (2021) code as “Gibberish” or “Non-sequiturs,” and follow their general coding rules for these responses:

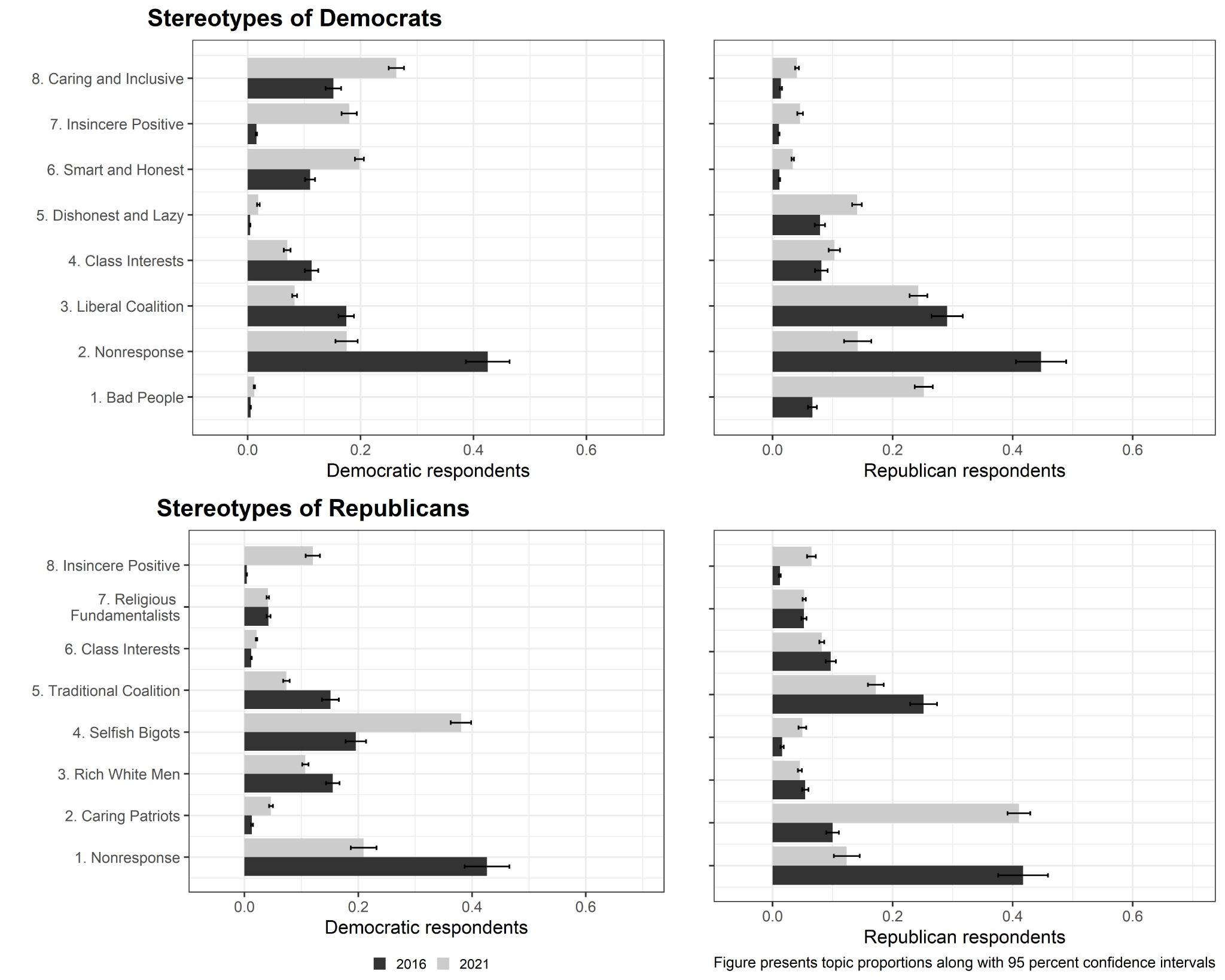
1. Responsive: Answers that included something that could be interpreted as a name (even if an incorrect name) or a description of a person. Examples: “John Kerry”, “Hillary Clinton”, “gates”, “The lying Clinton scum.”, “Blinken”, “Nancy Pelosi”, “A Communist”.
2. Don’t Know/refused: Answers that indicated the respondent did not know or chose not to provide an answer. Examples: “Don’t Know,” “idk,”, “n/a”, “Don’t care”, “?”
3. Gibberish: These responses were numbers, letters, or just punctuation that did not form real words. Example: “77339”, “Ddf”, “wertyguhijio”.
4. Non-Sequitur: Answers that were not blank but did not include a name, description of a person, a don’t know or refusal, or gibberish. Examples: “Baby love you too baby girl I love you too baby girl”, “good”, “Illinois”, “Taxes”, “yes”, “none”, “afw”.

Table G.1 shows the percentage of answers that fell into each category in each sample. We do find a higher percentage of “insincere” responses in 2021, though these responses still make up a relatively small proportion of the overall sample. These respondents were disproportionately likely to be categorized in the “Insincere Positive” categories. 3% of insincere respondents in 2016 and 25% of insincere respondents in 2021 were categorized by the STM in the “insincere positive” for their responses about Democrats, and 1% of insincere respondents in 2016 and 18% of insincere respondents in 2021 were categorized in the “Insincere Positive” category for their responses about Republicans.

| Response Type | 2016 Sample | 2021 Sample |
| --- | --- | --- |
| Gibberish | 5 (0.6%) | 14 (1.2%) |
| Non-Sequitur | 6 (0.8%) | 52 (4.4%) |
| Insincere (Gibberish + Non-Sequitur) | 11 (1.4%) | 66 (5.6%) |

**Table G1. Insincere responses**

However, the fact that even in 2021 these respondents made up only 5.6% of the sample means that removing them from the sample has relatively little impact on the overall results. Figure G1 replicates Figure G2 above with insincere respondents removed – the biggest change is 1.1 percentage points and most are significantly less than 1%.

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**Figure G1: Unweighted mean estimates of topic prevalence with insincere responses removed.**

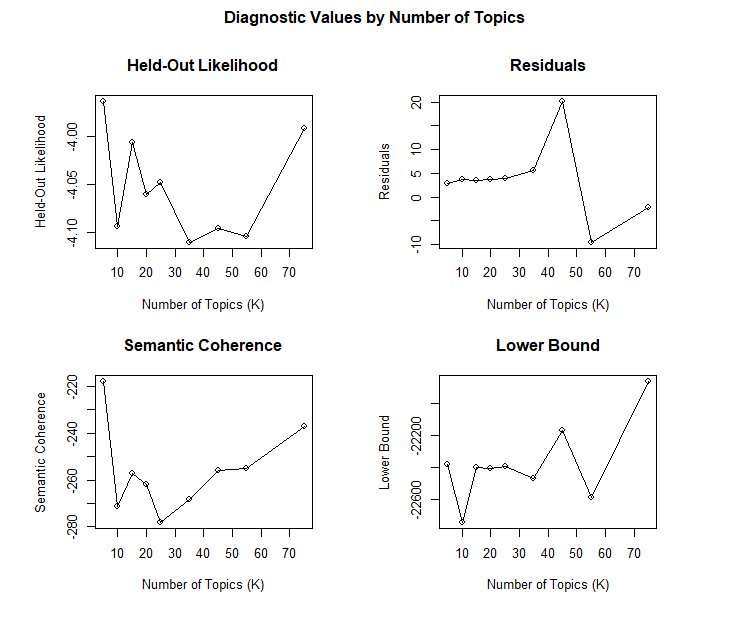
**Appendix H: Additional Topic Modeling Details**

As discussed in the main text, we use structural topic modeling to analyses these open-ended stereotypes of Republicans and Democrats. This section contains detailed information that does not fit into the main text about how we used the open-ended texts in the STM process and the decisions that we made as we used these topic models. The steps described here are included in our pre-analysis plans.[[4]](#footnote-3) Before using any STM procedures, we recorded blank responses and statements like “don’t know”, “NA”, and “None” as the word “Nonresponse”. This allows us to examine instances and correlates of nonresponse in a way we could not do if we treated these data as missing. We did not employ any other recoding or modification of these open-ended texts.

Next, we followed the pre-processing steps recommended by the developers or STM and included as defaults in the STM package in R. This involves removing stop words, punctuation, and numbers from the text. It also puts the terms all in lowercase, drops words occurring less than 5 times, and stemming the words (as noted in the main text). Both of these steps—recoding nonresponse and using the pre-processing defaults from STM—parallel the approach used by Rothschild et al (2019) in their published work on this topic.

The process we used, which is described in our pre-analysis plan, involved considering topic models with between 5 and 75 topics. Using the statistical measures of model performance generated by the STM analysis (namely semantic coherence and exclusivity), we narrowed this larger range into a smaller range of topics and repeated the comparison of statistics. The following tables and figures provide the results of our model searches.

**Figure H.1: Wide model search for stereotypes about Democrats:**

**

**Table H.1: Wide model search for stereotypes about Democrats:**

*|K |exclus |semcoh |heldout |residual |bound |lbound |em.its |*

*|:--|:--------|:---------|:---------|:---------|:---------|:---------|:------|*

*|5 |9.355372 |-217.8014 |-3.96333 |2.90219 |-22389.83 |-22385.04 |106 |*

*|10 |9.733468 |-271.2521 |-4.094444 |3.621387 |-22764.52 |-22749.42 |85 |*

*|15 |9.252025 |-257.1203 |-4.006671 |3.504907 |-22425.81 |-22397.91 |103 |*

*|20 |9.212581 |-261.7928 |-4.060171 |3.717873 |-22451.03 |-22408.7 |145 |*

*|25 |8.869157 |-278.2303 |-4.048367 |3.962594 |-22454.75 |-22396.75 |109 |*

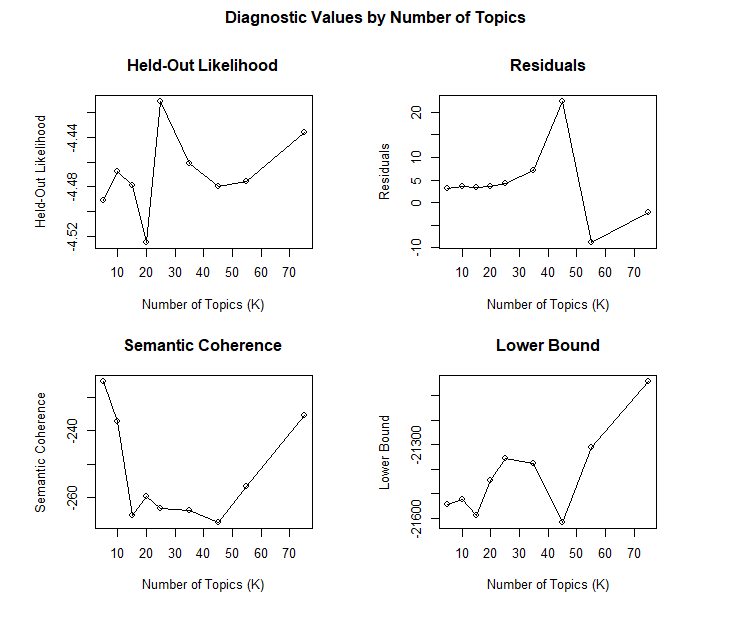
*|35 |8.423514 |-268.4229 |-4.110844 |5.660161 |-22562.22 |-22470.08 |75 |*

*|45 |8.270005 |-255.8361 |-4.096253 |20.17372 |-22298.75 |-22169.63 |161 |*

*|55 |8.404615 |-255.2349 |-4.104669 |-9.601161 |-22756.08 |-22587.75 |60 |*

*|75 |8.90323 |-237.1278 |-3.991842 |-2.291379 |-22109.67 |-21857.78 |254 |*

**Figure H.2: Wide model search for stereotypes about Republicans:**



**Table H.2: Wide model search for stereotypes about Republicans:**

|K |exclus |semcoh |heldout |residual |bound |lbound |em.its |

|:--|:--------|:---------|:---------|:---------|:---------|:---------|:------|

|5 |9.294419 |-225.285 |-4.491272 |3.14817 |-21547.34 |-21542.55 |97 |

|10 |9.228187 |-237.0981 |-4.467293 |3.502442 |-21539.86 |-21524.76 |104 |

|15 |9.260182 |-265.2831 |-4.479219 |3.404675 |-21616.89 |-21588.99 |126 |

|20 |9.222685 |-259.7062 |-4.525082 |3.685663 |-21488.47 |-21446.13 |165 |

|25 |8.440863 |-263.0198 |-4.410724 |4.144744 |-21416.53 |-21358.53 |149 |

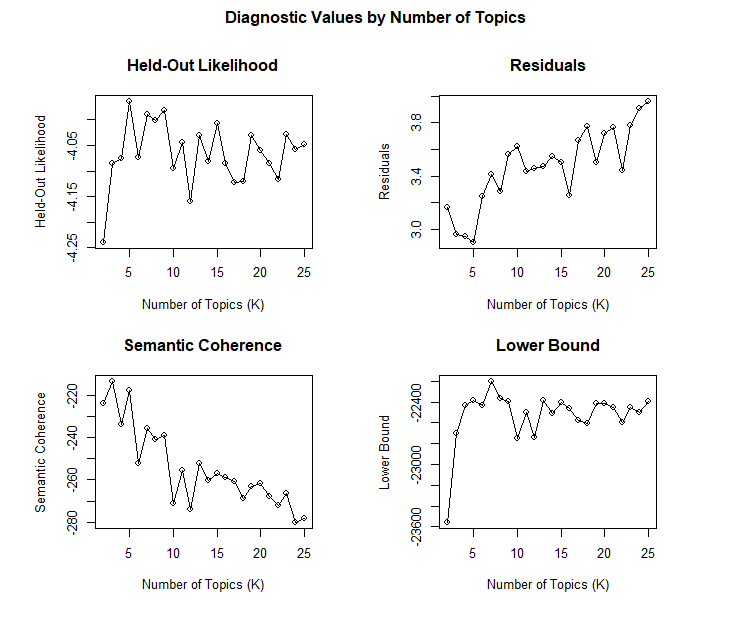
|35 |8.105933 |-263.8456 |-4.461295 |7.030996 |-21469.17 |-21377.03 |153 |

|45 |8.502273 |-267.3849 |-4.479738 |22.39683 |-21747.77 |-21618.64 |90 |

|55 |8.590143 |-256.6553 |-4.475865 |-8.81046 |-21479.99 |-21311.67 |221 |

|75 |8.684687 |-235.3049 |-4.435645 |-2.218952 |-21294.43 |-21042.54 |289 |

**Figure H.3 Narrower model search about Democrats:**

**

**Table H.3 Narrower model search about Democrats:**

*|K |exclus |semcoh |heldout |residual |bound |lbound |em.its |*

*|:--|:--------|:---------|:---------|:--------|:---------|:---------|:------|*

*|2 |7.580747 |-223.8736 |-4.240252 |3.165941 |-23561.34 |-23560.65 |57 |*

*|3 |8.67842 |-213.4483 |-4.084918 |2.959621 |-22699.15 |-22697.35 |85 |*

*|4 |9.104238 |-233.5625 |-4.074698 |2.949556 |-22436.16 |-22432.98 |128 |*

*|5 |9.355372 |-217.8014 |-3.96333 |2.90219 |-22389.83 |-22385.04 |106 |*

*|6 |9.566438 |-252.1853 |-4.073577 |3.250509 |-22441.74 |-22435.16 |131 |*

*|7 |9.513211 |-235.7473 |-3.989879 |3.416323 |-22207.84 |-22199.32 |148 |*

*|8 |9.483365 |-241.0392 |-4.000278 |3.288967 |-22375.42 |-22364.81 |105 |*

*|9 |9.571426 |-239.1959 |-3.98088 |3.559753 |-22401.51 |-22388.71 |133 |*

*|10 |9.733468 |-271.2521 |-4.094444 |3.621387 |-22764.52 |-22749.42 |85 |*

*|11 |9.474708 |-255.6871 |-4.043618 |3.438872 |-22511.61 |-22494.11 |100 |*

*|12 |9.667229 |-274.0789 |-4.159213 |3.455844 |-22756.68 |-22736.7 |61 |*

*|13 |9.345763 |-252.3101 |-4.031022 |3.473467 |-22404.19 |-22381.63 |128 |*

*|14 |9.326149 |-260.0587 |-4.082203 |3.548987 |-22536.11 |-22510.92 |108 |*

*|15 |9.252025 |-257.1203 |-4.006671 |3.504907 |-22425.81 |-22397.91 |103 |*

*|16 |9.2868 |-258.8106 |-4.084817 |3.254658 |-22491.05 |-22460.38 |120 |*

*|17 |9.219304 |-260.596 |-4.122432 |3.669761 |-22613.12 |-22579.62 |89 |*

*|18 |8.85613 |-268.6785 |-4.11973 |3.770741 |-22639.7 |-22603.31 |135 |*

*|19 |9.158869 |-262.9235 |-4.030692 |3.503846 |-22454.53 |-22415.19 |103 |*

*|20 |9.212581 |-261.7928 |-4.060171 |3.717873 |-22451.03 |-22408.7 |145 |*

*|21 |9.15789 |-267.8363 |-4.08537 |3.764106 |-22499.42 |-22454.04 |185 |*

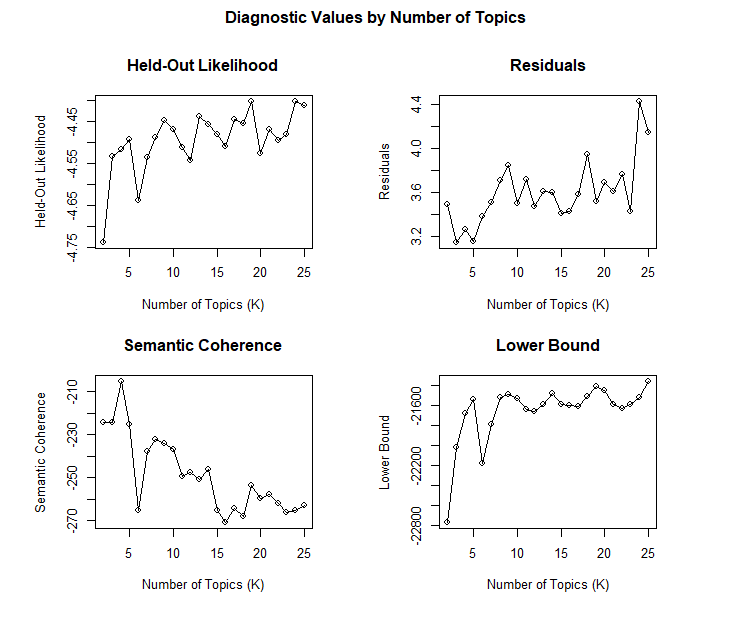
*|22 |9.225845 |-271.9836 |-4.117219 |3.444743 |-22641.74 |-22593.26 |56 |*

*|23 |8.850379 |-266.1925 |-4.028075 |3.779695 |-22497.57 |-22445.96 |95 |*

*|24 |8.587963 |-280.1748 |-4.058457 |3.905206 |-22550.07 |-22495.29 |98 |*

*|25 |8.869157 |-278.2303 |-4.048367 |3.962594 |-22454.75 |-22396.75 |109 |*

**Figure H.4 Narrower model search about Republicans:**

**

**Table H.4 Narrower model search about Republicans:**

*|K |exclus |semcoh |heldout |residual |bound |lbound |em.its |*

*|:--|:--------|:---------|:---------|:--------|:---------|:---------|:------|*

*|2 |8.348247 |-224.6255 |-4.737577 |3.489559 |-22770.83 |-22770.13 |104 |*

*|3 |8.736587 |-224.4467 |-4.531954 |3.14186 |-22019.5 |-22017.71 |63 |*

*|4 |9.305584 |-205.2869 |-4.516483 |3.265302 |-21680.63 |-21677.46 |106 |*

*|5 |9.294419 |-225.285 |-4.491272 |3.14817 |-21547.34 |-21542.55 |97 |*

*|6 |9.547445 |-265.5072 |-4.638304 |3.381088 |-22181.47 |-22174.89 |80 |*

*|7 |9.572978 |-237.9758 |-4.53586 |3.504532 |-21794.43 |-21785.9 |101 |*

*|8 |9.560112 |-232.232 |-4.486697 |3.703398 |-21531.49 |-21520.89 |77 |*

*|9 |9.600207 |-234.259 |-4.446267 |3.84365 |-21497.73 |-21484.93 |133 |*

*|10 |9.228187 |-237.0981 |-4.467293 |3.502442 |-21539.86 |-21524.76 |104 |*

*|11 |9.668881 |-249.262 |-4.51076 |3.720642 |-21658.78 |-21641.28 |77 |*

*|12 |9.313972 |-247.4237 |-4.542033 |3.469484 |-21677.29 |-21657.3 |87 |*

*|13 |9.329244 |-250.8785 |-4.437765 |3.603558 |-21613.73 |-21591.18 |130 |*

*|14 |9.179891 |-246.2978 |-4.455608 |3.595163 |-21501.61 |-21476.41 |112 |*

*|15 |9.260182 |-265.2831 |-4.479219 |3.404675 |-21616.89 |-21588.99 |126 |*

*|16 |9.258675 |-270.9843 |-4.509263 |3.42735 |-21629.22 |-21598.55 |99 |*

*|17 |9.558545 |-264.3498 |-4.444655 |3.57956 |-21638.56 |-21605.05 |83 |*

*|18 |9.137396 |-267.9904 |-4.453078 |3.940965 |-21544.37 |-21507.97 |157 |*

*|19 |8.991857 |-253.899 |-4.40186 |3.520476 |-21451.66 |-21412.32 |98 |*

*|20 |9.222685 |-259.7062 |-4.525082 |3.685663 |-21488.47 |-21446.13 |165 |*

*|21 |9.065344 |-258.0628 |-4.46754 |3.60701 |-21630.49 |-21585.11 |114 |*

*|22 |8.677189 |-262.0905 |-4.494693 |3.766549 |-21679.71 |-21631.24 |113 |*

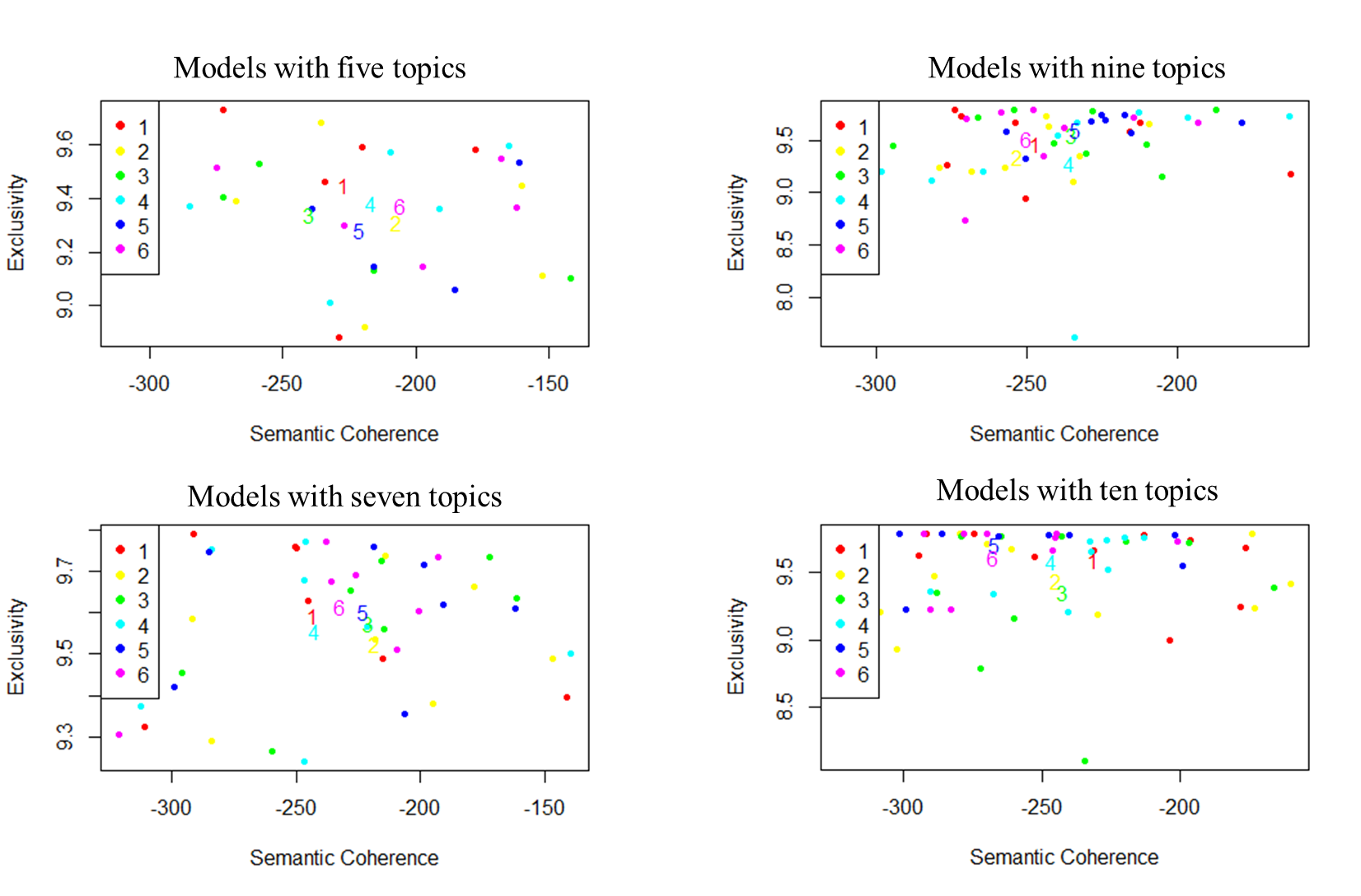
*|23 |8.852155 |-266.3465 |-4.480031 |3.425996 |-21642.25 |-21590.64 |75 |*

*|24 |8.477546 |-265.4178 |-4.400721 |4.43017 |-21570.4 |-21515.62 |131 |*

*|25 |8.440863 |-263.0198 |-4.410724 |4.144744 |-21416.53 |-21358.53 |149 |*

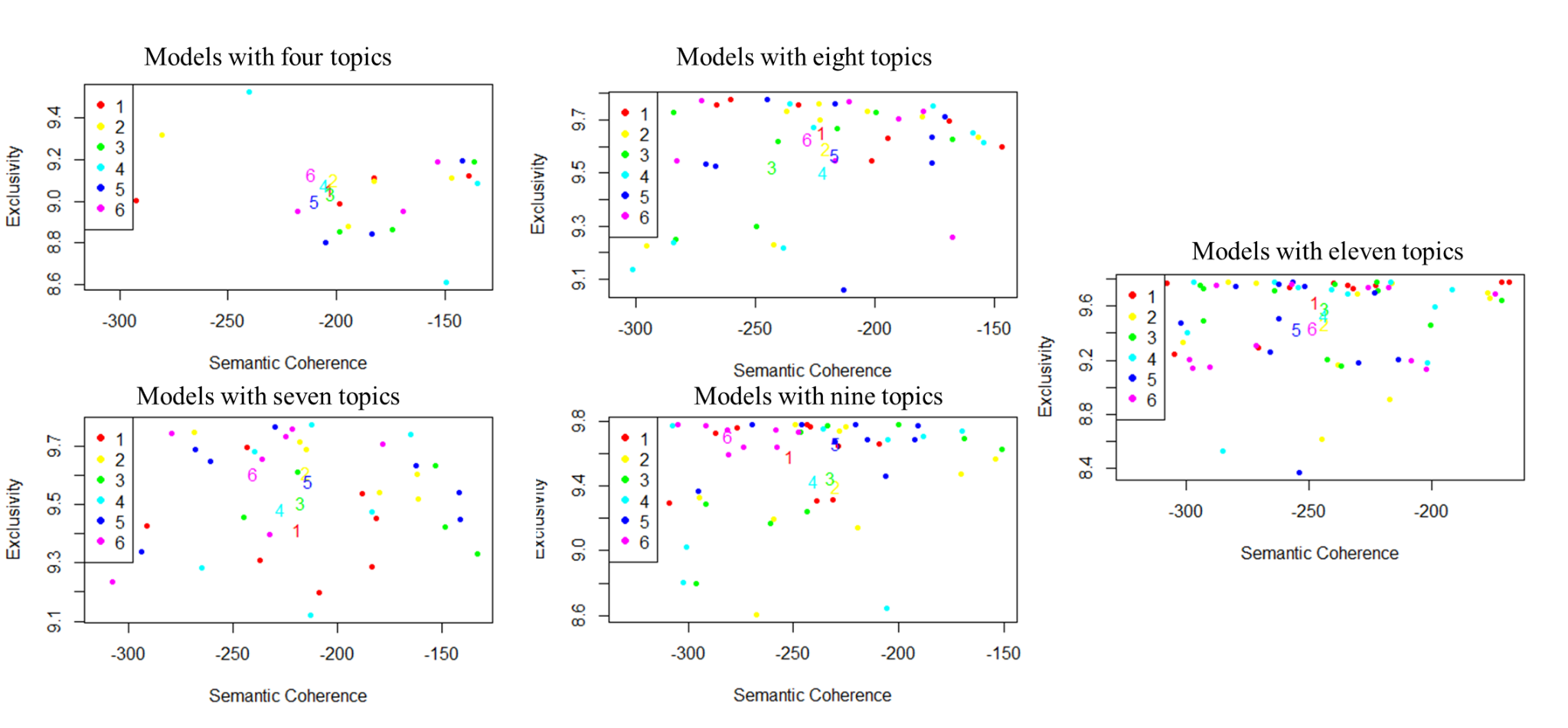
At this stage, we selected a set of specific models to consider more closely. This first involved choosing models with a specific number of topics and running multiple iterations of that topic model. We selected the number of topics in these analyses based on which models seemed to perform best in the model searches above. We did not constrain this process to require models with the same number of topics for stereotypes of Republicans and Democrats. From this process, we then examined the semantic coherence and exclusivity of those models to determine what specific model (of each topic number) to evaluate. Because this process is still removed from the actual words and themes associated with these models, it allows us to choose a well-performing model without the temptation to select topic models that emphasize themes favorable to our theories and hypotheses. The figures below present the results of these analyses; in these figures, the numbers indicate the top performing models for each set.

**Figure H.5, Democratic models with specific numbers of topics**

****

Next, we evaluated the specific results from the top models for each number of topics. We chose the specific versions of each number of topics that performed best in the analyses summarized in the figures above. It was at this stage that we first considered the specific themes and terms generated by the STM procedures. For stereotypes about Democrats, we considered three models with five topics, three models with seven topics, two models with nine topics, and one model with ten topics. For stereotypes about Republicans, we evaluated two models with four topics, three models with seven topics, two models with eight topics, one model with nine topics, and three models with eleven topics. The detailed model results follow in the tables below; the version numbers in these tables refer to the numbers in figures H.5 and H.6.

**Figure H.6, Republican models with specific numbers of topics**

****

We then chose our final models - version five of the five topic model about Democrats and version six of the four topic model about Republicans - based on comparing the content of these models and exemplar documents for each. As shown in tables H.5 and H.6, most of the major themes in these topics are consistent across the different versions of these models, suggesting important core themes that are not contingent on our modeling choices. This also gives some evidence that the topic modeling works reasonably well for the number and length of documents we have here; if either length or the number of documents was causing problems for the topic modeling, we would expect to observe instability in the topic content and interpretation of the STM results from version to version. We also note that here we are using a comparable number of documents to many published, methodological discussions of structural topic modeling (Roberts et al. 2014).

**Table H.5. Detailed topic model results for Democratic Stereotypes**

**Five topic models**

*Version 2:*

Topic 1 Top Words:

Highest Prob: nonrespons, know, dont, money, conserv, moder, yes

FREX: nonrespons, dont, know, money, conserv, moder, yes

Lift: nonrespons, know, dont, donã¢â‚¬â„¢t, brave, get, just

Score: nonrespons, know, dont, ethnic, thiev, immor, awar

Topic 2 Top Words:

Highest Prob: good, nice, biden, great, cool, support, like

FREX: great, good, like, nice, cool, biden, awesom

Lift: amaz, awesom, joe, like, cool, great, good

Score: good, nice, great, biden, cool, like, joe

Topic 3 Top Words:

Highest Prob: care, smart, open, honest, fair, mind, help

FREX: honest, help, care, inclus, intellig, hope, thought

Lift: concern, thought, empathet, honest, toler, hope, inclus

Score: care, smart, honest, open, fair, help, intellig

Topic 4 Top Words:

Highest Prob: liber, poor, progress, left, minor, class, young

FREX: minor, class, pro, union, middl, young, liber

Lift: ethnic, women, pro, collar, union, minor, wing

Score: liber, poor, minor, left, class, young, progress

Topic 5 Top Words:

Highest Prob: socialist, lazi, stupid, dumb, liar, tax, rich

FREX: stupid, dishonest, lazi, idiot, selfish, unrealist, dumb

Lift: moron, evil, untrustworthi, cheat, crook, sad, rude

Score: socialist, lazi, stupid, dumb, liar, tax, ignor

*Version 5:*

Topic 1 Top Words:

Highest Prob: nonrespons, like, yes, stubborn, bad, conserv, big

FREX: nonrespons, like, yes, stubborn, bad, conserv, big

Lift: nonrespons, like, yes, awar, bad, best, chang

Score: nonrespons, like, yes, brave, just, real, argument

Topic 2 Top Words:

Highest Prob: care, good, smart, honest, nice, help, support

FREX: honest, good, great, help, nice, cool, intellig

Lift: reliabl, brave, great, awesom, real, amaz, cool

Score: good, care, smart, honest, nice, help, support

Topic 3 Top Words:

Highest Prob: liber, open, progress, mind, educ, poor, minor

FREX: open, educ, middl, mind, progress, class, minor

Lift: middl, women, urban, collar, worker, class, educ

Score: liber, open, progress, educ, mind, minor, class

Topic 4 Top Words:

Highest Prob: liber, ignor, mean, selfish, uninform, greedi, unrealist

FREX: selfish, greedi, mean, gullibl, ignor, sheep, uninform

Lift: arrog, sheep, misinform, gullibl, greedi, selfish, unrealist

Score: ignor, mean, selfish, uninform, unrealist, greedi, entitl

Topic 5 Top Words:

Highest Prob: liber, socialist, lazi, stupid, left, dumb, liar

FREX: lazi, dumb, stupid, welfar, socialist, liar, wrong

Lift: sad, wrong, welfar, argument, anti, evil, stupid

Score: socialist, lazi, stupid, dumb, liar, tax, left

*Version 6:*

Topic 1 Top Words:

Highest Prob: liber, socialist, left, poor, lazi, tax, minor

FREX: socialist, uninform, entitl, tax, unrealist, welfar, lazi

Lift: intoler, freeload, close, emot, entitl, unrealist, uninform

Score: liber, socialist, lazi, poor, tax, left, uninform

Topic 2 Top Words:

Highest Prob: care, good, smart, honest, nice, fair, help

FREX: honest, good, great, nice, cool, help, intellig

Lift: reliabl, amaz, awesom, real, great, brave, cool

Score: good, care, smart, honest, nice, fair, help

Topic 3 Top Words:

Highest Prob: nonrespons, know, like, dont, yes, rich, money

FREX: nonrespons, know, dont, like, yes, rich, money

Lift: nonrespons, know, dont, yes, like, donã¢â‚¬â„¢t, abort

Score: nonrespons, know, like, dont, yes, intoler, brave

Topic 4 Top Words:

Highest Prob: liber, open, progress, mind, educ, class, peopl

FREX: open, middl, class, educ, mind, progress, pro

Lift: middl, choic, women, class, inclus, open, divers

Score: liber, open, progress, educ, mind, class, middl

Topic 5 Top Words:

Highest Prob: stupid, dumb, biden, liar, ignor, mean, weak

FREX: stupid, ignor, dumb, crazi, idiot, joe, selfish

Lift: untrustworthi, evil, sad, crook, moron, fake, lie

Score: stupid, dumb, biden, liar, ignor, dishonest, selfish

**Seven topic models**

*Version 2:*

Topic 1 Top Words:

Highest Prob: care, liber, smart, open, mind, progress, fair

FREX: care, open, inclus, help, intellig, fair, mind

Lift: empathet, concern, averag, inclus, thought, help, care

Score: care, open, fair, smart, mind, help, progress

Topic 2 Top Words:

Highest Prob: liber, socialist, left, lazi, tax, poor, uninform

FREX: socialist, uninform, tax, left, unrealist, welfar, lazi

Lift: emot, unrealist, entitl, socialist, uninform, welfar, idealist

Score: liber, socialist, left, lazi, tax, uninform, welfar

Topic 3 Top Words:

Highest Prob: liber, educ, poor, peopl, class, middl, minor

FREX: class, educ, middl, peopl, pro, poor, women

Lift: choic, women, middl, class, pro, educ, work

Score: liber, educ, class, peopl, poor, middl, pro

Topic 4 Top Words:

Highest Prob: honest, biden, know, joe, dont, obama, inform

FREX: know, dont, honest, joe, biden, obama, inform

Lift: dont, know, joe, obama, biden, honest, inform

Score: honest, biden, know, joe, dont, obama, inform

Topic 5 Top Words:

Highest Prob: good, nice, great, cool, like, support, strong

FREX: cool, like, good, great, nice, awesom, yes

Lift: awesom, yes, like, great, cool, good, nice

Score: good, nice, great, cool, like, yes, support

Topic 6 Top Words:

Highest Prob: nonrespons, money, moder, abort, white, polit, posit

FREX: nonrespons, money, moder, abort, white, polit, posit

Lift: nonrespons, donã¢â‚¬â„¢t, argument, best, brave, chang, delusion

Score: nonrespons, averag, hate, untrustworthi, evil, sad, emot

Topic 7 Top Words:

Highest Prob: stupid, dumb, liar, rich, ignor, weak, mean

FREX: stupid, idiot, dishonest, ignor, liar, dumb, stubborn

Lift: untrustworthi, evil, sad, fake, hate, stupid, idiot

Score: stupid, dumb, liar, rich, ignor, idiot, dishonest

*Version 3:*

Topic 1 Top Words:

Highest Prob: care, smart, honest, fair, help, intellig, compassion

FREX: honest, care, help, fair, smart, thought, compassion

Lift: thought, honest, help, empathet, generous, care, fair

Score: care, smart, honest, fair, help, intellig, compassion

Topic 2 Top Words:

Highest Prob: open, progress, mind, peopl, biden, social, inclus

FREX: open, biden, inclus, joe, mind, obama, democrat

Lift: joe, obama, parti, open, toler, inclus, biden

Score: open, mind, progress, peopl, biden, inclus, democrat

Topic 3 Top Words:

Highest Prob: good, nice, great, cool, support, like, trustworthi

FREX: great, cool, good, nice, like, reliabl, trustworthi

Lift: awesom, great, cool, like, good, nice, reliabl

Score: good, nice, great, cool, like, trustworthi, support

Topic 4 Top Words:

Highest Prob: nonrespons, rich, money, conserv, yes, big, loud

FREX: nonrespons, rich, money, conserv, yes, big, loud

Lift: nonrespons, donã¢â‚¬â„¢t, argument, best, ethnic, fun, get

Score: nonrespons, hispan, close, awesom, arrog, old, self

Topic 5 Top Words:

Highest Prob: socialist, lazi, stupid, dumb, liar, tax, ignor

FREX: stupid, lazi, dishonest, ignor, unrealist, selfish, idiot

Lift: arrog, dishonest, gullibl, unrealist, stupid, selfish, idiot

Score: socialist, lazi, stupid, dumb, liar, tax, ignor

Topic 6 Top Words:

Highest Prob: left, black, work, american, know, crazi, dont

FREX: know, left, dont, black, american, wing, anti

Lift: dont, hispan, know, wing, anti, american, left

Score: left, black, work, american, know, crazi, dont

Topic 7 Top Words:

Highest Prob: liber, poor, minor, class, young, middl, pro

FREX: minor, pro, liber, middl, young, class, women

Lift: women, pro, minor, middl, hippi, young, class

Score: liber, minor, class, young, middl, pro, poor

*Version 5:*

Topic 1 Top Words:

Highest Prob: stupid, lazi, dumb, liar, ignor, mean, dishonest

FREX: stupid, ignor, dumb, dishonest, lazi, idiot, mean

Lift: moron, evil, hate, confus, stupid, ignor, dishonest

Score: stupid, dumb, ignor, dishonest, mean, lazi, idiot

Topic 2 Top Words:

Highest Prob: nonrespons, rich, democrat, like, crazi, white, abort

FREX: nonrespons, rich, democrat, like, white, abort, spender

Lift: nonrespons, like, donã¢â‚¬â„¢t, crazi, democrat, forward, fun

Score: nonrespons, donã¢â‚¬â„¢t, moron, hate, confus, evil, spend

Topic 3 Top Words:

Highest Prob: open, mind, left, liber, welfar, wing, close

FREX: mind, open, left, wing, welfar, close, self

Lift: wing, mind, open, close, left, welfar, handout

Score: open, mind, left, wing, close, welfar, liber

Topic 4 Top Words:

Highest Prob: black, blue, american, stubborn, uninform, collar, yes

FREX: stubborn, yes, collar, american, black, blue, loud

Lift: collar, stubborn, yes, loud, opinion, old, american

Score: black, blue, american, stubborn, collar, yes, loud

Topic 5 Top Words:

Highest Prob: liber, socialist, progress, minor, young, social, pro

FREX: pro, young, minor, socialist, govern, liber, free

Lift: pro, govern, spend, choic, free, young, tax

Score: liber, socialist, minor, young, progress, social, pro

Topic 6 Top Words:

Highest Prob: care, good, smart, honest, nice, fair, help

FREX: good, honest, great, help, nice, cool, care

Lift: great, cool, honest, trustworthi, good, thought, love

Score: good, care, smart, honest, nice, help, support

Topic 7 Top Words:

Highest Prob: poor, educ, peopl, class, middl, work, union

FREX: class, middl, educ, work, know, peopl, poor

Lift: middl, class, dont, know, work, worker, peopl

Score: poor, educ, class, peopl, middl, work, union

**Nine topic models**

*Version 3:*

Topic 1 Top Words:

Highest Prob: care, help, support, peopl, intellig, blue, collar

FREX: help, care, support, collar, blue, intellig, peopl

Lift: help, collar, care, blue, support, intellig, unbias

Score: care, help, support, blue, collar, intellig, peopl

Topic 2 Top Words:

Highest Prob: fair, class, biden, middl, work, equal, compassion

FREX: class, middl, biden, know, fair, equal, work

Lift: dont, know, middl, obama, class, joe, equal

Score: fair, class, biden, middl, work, equal, compassion

Topic 3 Top Words:

Highest Prob: poor, lazi, liar, black, tax, liber, radic

FREX: liar, lazi, tax, entitl, poor, black, radic

Lift: entitl, tax, liar, self, lazi, radic, black

Score: poor, lazi, liar, tax, black, entitl, radic

Topic 4 Top Words:

Highest Prob: good, nice, great, cool, like, democrat, interest

FREX: good, great, cool, like, nice, democrat, interest

Lift: like, cool, great, good, nice, interest, democrat

Score: good, nice, great, cool, like, interest, democrat

Topic 5 Top Words:

Highest Prob: open, smart, mind, kind, peac, hope, thought

FREX: open, mind, peac, smart, kind, think, hope

Lift: open, think, mind, peac, hope, kind, thought

Score: open, smart, mind, kind, peac, hope, think

Topic 6 Top Words:

Highest Prob: socialist, left, stupid, dumb, liber, ignor, mean

FREX: stupid, ignor, socialist, dumb, selfish, dishonest, left

Lift: gullibl, stupid, greedi, ignor, unrealist, selfish, dishonest

Score: socialist, stupid, left, dumb, ignor, mean, dishonest

Topic 7 Top Words:

Highest Prob: nonrespons, rich, conserv, yes, uneduc, fake, loud

FREX: nonrespons, rich, conserv, yes, uneduc, fake, loud

Lift: nonrespons, donã¢â‚¬â„¢t, argument, cheat, fake, fun, get

Score: nonrespons, truth, self, gullibl, reliabl, empathet, greedi

Topic 8 Top Words:

Highest Prob: honest, american, trustworthi, trust, reliabl, right, empathet

FREX: honest, trustworthi, trust, american, reliabl, right, truth

Lift: trustworthi, honest, truth, trust, reliabl, right, empathet

Score: honest, american, trustworthi, trust, reliabl, right, empathet

Topic 9 Top Words:

Highest Prob: liber, progress, educ, minor, young, social, pro

FREX: minor, young, liber, pro, educ, choic, progress

Lift: pro, choic, young, minor, social, educ, progress

Score: liber, minor, educ, progress, young, social, pro

*Version 5:*

Topic 1 Top Words:

Highest Prob: open, mind, smart, equal, blue, democrat, young

FREX: open, mind, equal, democrat, blue, smart, women

Lift: equal, open, mind, democrat, collar, blue, women

Score: open, mind, smart, equal, blue, democrat, women

Topic 2 Top Words:

Highest Prob: nonrespons, conserv, racist, uneduc, self, fake, loud

FREX: nonrespons, conserv, racist, uneduc, self, fake, loud

Lift: nonrespons, donã¢â‚¬â„¢t, delusion, fake, fun, get, hate

Score: nonrespons, arrog, wrong, sheep, empathet, think, yes

Topic 3 Top Words:

Highest Prob: support, understand, depend, liber, love, moder, peac

FREX: support, understand, depend, moder, love, peac, idealist

Lift: support, moder, understand, depend, love, peac, freedom

Score: support, understand, depend, moder, love, peac, liber

Topic 4 Top Words:

Highest Prob: good, nice, great, cool, like, interest, kind

FREX: great, good, like, cool, nice, yes, interest

Lift: yes, like, great, cool, good, interest, nice

Score: good, nice, great, cool, like, interest, yes

Topic 5 Top Words:

Highest Prob: socialist, lazi, stupid, left, dumb, liar, rich

FREX: stupid, ignor, lazi, socialist, dishonest, liar, wrong

Lift: wrong, dishonest, ignor, gullibl, stupid, idiot, mean

Score: socialist, lazi, stupid, liar, left, ignor, dishonest

Topic 6 Top Words:

Highest Prob: poor, educ, peopl, class, biden, middl, work

FREX: class, middl, poor, peopl, biden, work, joe

Lift: dont, joe, middl, obama, know, class, biden

Score: poor, educ, peopl, class, biden, middl, work

Topic 7 Top Words:

Highest Prob: liber, pro, uninform, selfish, weak, naiv, young

FREX: uninform, unrealist, pro, naiv, selfish, entitl, choic

Lift: arrog, sheep, unrealist, entitl, greedi, uninform, naiv

Score: pro, uninform, selfish, naiv, choic, unrealist, entitl

Topic 8 Top Words:

Highest Prob: liber, minor, social, free, govern, divers, welfar

FREX: minor, liber, social, govern, free, divers, welfar

Lift: minor, social, liber, govern, urban, divers, environmentalist

Score: liber, minor, social, govern, free, divers, welfar

Topic 9 Top Words:

Highest Prob: care, honest, smart, help, fair, progress, intellig

FREX: honest, help, care, thought, inclus, intellig, fair

Lift: thought, honest, help, empathet, inclus, friend, care

Score: care, honest, help, smart, fair, inclus, intellig

**Ten topic models**

*Version 1:*

Topic 1 Top Words:

Highest Prob: free, bad, gullibl, idealist, think, liber, sheep

FREX: free, gullibl, idealist, bad, think, sheep, forward

Lift: free, gullibl, idealist, think, bad, sheep, heart

Score: free, bad, gullibl, idealist, think, sheep, liber

Topic 2 Top Words:

Highest Prob: nonrespons, money, conserv, fake, loud, abort, posit

FREX: nonrespons, money, conserv, fake, loud, abort, posit

Lift: nonrespons, donã¢â‚¬â„¢t, argument, best, fake, fun, get

Score: nonrespons, donã¢â‚¬â„¢t, crazi, younger, yes, idealist, think

Topic 3 Top Words:

Highest Prob: liber, poor, minor, union, black, women, blue

FREX: minor, poor, liber, union, black, women, blue

Lift: minor, union, poor, liber, women, black, uneduc

Score: liber, poor, minor, union, black, women, blue

Topic 4 Top Words:

Highest Prob: good, nice, great, cool, interest, strong, happi

FREX: good, great, cool, nice, interest, happi, strong

Lift: cool, great, good, nice, interest, amaz, awesom

Score: good, nice, great, cool, interest, happi, strong

Topic 5 Top Words:

Highest Prob: care, smart, honest, fair, help, intellig, kind

FREX: honest, help, care, intellig, smart, hope, thought

Lift: honest, thought, trustworthi, help, hope, intellig, peac

Score: care, smart, honest, fair, help, intellig, kind

Topic 6 Top Words:

Highest Prob: educ, class, young, middl, work, equal, divers

FREX: class, educ, middl, work, young, divers, equal

Lift: middl, class, divers, work, worker, educ, equal

Score: educ, class, young, middl, work, equal, divers

Topic 7 Top Words:

Highest Prob: peopl, support, pro, rich, democrat, choic, polit

FREX: pro, peopl, choic, democrat, rich, support, polit

Lift: choic, democrat, pro, rich, peopl, polit, support

Score: peopl, support, pro, rich, democrat, choic, polit

Topic 8 Top Words:

Highest Prob: open, progress, mind, social, liber, govern, friend

FREX: open, mind, progress, social, govern, friend, liber

Lift: mind, open, progress, govern, social, friend, big

Score: open, progress, mind, social, govern, friend, liber

Topic 9 Top Words:

Highest Prob: biden, know, like, joe, dont, obama, yes

FREX: know, like, joe, biden, dont, yes, obama

Lift: joe, like, dont, yes, know, biden, obama

Score: biden, know, like, joe, dont, obama, yes

Topic 10 Top Words:

Highest Prob: socialist, lazi, stupid, left, dumb, liar, tax

FREX: stupid, lazi, dishonest, socialist, selfish, liar, uninform

Lift: dishonest, stupid, selfish, greedi, welfar, uninform, stubborn

Score: socialist, lazi, stupid, liar, dumb, dishonest, tax

**Table H.6. Detailed topic model results for Republican Stereotypes**

**Four topic models**

*Version 2:*

Topic 1 Top Words:

Highest Prob: conserv, white, religi, right, wealthi, old, christian

FREX: pro, religi, life, middl, educ, independ, conserv

Lift: fiscal, constitut, life, prolif, pro, rural, frugal

Score: conserv, religi, right, white, pro, educ, christian

Topic 2 Top Words:

Highest Prob: smart, good, patriot, honest, american, strong, care

FREX: great, loyal, kind, nice, good, help, awesom

Lift: correct, posit, hope, great, awesom, kind, humbl

Score: good, smart, honest, american, patriot, strong, care

Topic 3 Top Words:

Highest Prob: rich, racist, selfish, white, trump, ignor, mind

FREX: selfish, stupid, racist, dishonest, greedi, mean, uneduc

Lift: sexist, evil, ugli, unreli, uninform, dishonest, uneduc

Score: racist, rich, selfish, trump, ignor, liar, bad

Topic 4 Top Words:

Highest Prob: nonrespons, yes, peopl, liber, concern, republican, love

FREX: nonrespons, yes, peopl, liber, concern, republican, love

Lift: nonrespons, yes, blue, bold, calm, concern, constitutionalist

Score: nonrespons, yes, sure, dont, correct, prolif, hope

*Version 6:*

Topic 1 Top Words:

Highest Prob: smart, patriot, honest, american, strong, care, good

FREX: honest, patriot, american, freedom, smart, hardwork, loyal

Lift: correct, god, logic, leader, understand, freedom, knowledg

Score: smart, patriot, honest, american, strong, care, loyal

Topic 2 Top Words:

Highest Prob: conserv, rich, white, religi, wealthi, old, mind

FREX: religi, pro, old, wealthi, close, life, white

Lift: male, life, owner, fashion, rural, evangel, fiscal

Score: conserv, white, rich, religi, wealthi, old, mind

Topic 3 Top Words:

Highest Prob: racist, selfish, good, trump, liar, bad, stupid

FREX: dishonest, bad, dumb, selfish, stupid, hate, liar

Lift: sad, demand, ugli, evil, dishonest, unreli, negat

Score: racist, selfish, bad, liar, stupid, good, trump

Topic 4 Top Words:

Highest Prob: nonrespons, like, less, liber, red, follow, moder

FREX: nonrespons, like, less, liber, red, follow, moder

Lift: nonrespons, like, bold, calm, cold, constitutionalist, determin

Score: nonrespons, like, correct, demand, understand, moron, fashion

**Seven topic models**

*Version 2:*

Topic 1 Top Words:

Highest Prob: nonrespons, bore, liber, republican, moral, trust, law

FREX: nonrespons, bore, liber, republican, moral, trust, law

Lift: nonrespons, sure, aggress, bore, calm, dedic, faith

Score: nonrespons, unreli, close-mind, god, yes, bold, fiscal

Topic 2 Top Words:

Highest Prob: conserv, religi, wealthi, right, educ, pro, class

FREX: religi, pro, educ, middl, conserv, class, wealthi

Lift: fiscal, middl, govern, older, pro, life, religi

Score: conserv, religi, wealthi, educ, pro, class, right

Topic 3 Top Words:

Highest Prob: rich, white, gun, stubborn, money, old, anti

FREX: rich, white, gun, male, money, anti, men

Lift: men, rich, redneck, male, anti, money, white

Score: rich, white, gun, money, stubborn, anti, old

Topic 4 Top Words:

Highest Prob: smart, patriot, honest, american, care, strong, loyal

FREX: patriot, honest, smart, care, loyal, fair, american

Lift: god, freedom, patriot, honest, fair, loyal, care

Score: smart, patriot, honest, care, american, strong, loyal

Topic 5 Top Words:

Highest Prob: trump, stupid, dumb, crazi, dont, wrong, hard

FREX: stupid, dont, trump, dumb, donald, know, crazi

Lift: know, donald, dont, negat, trump, dumb, stupid

Score: trump, stupid, dumb, crazi, dont, wrong, donald

Topic 6 Top Words:

Highest Prob: racist, selfish, ignor, liar, bad, greedi, mind

FREX: selfish, racist, dishonest, greedi, bad, ignor, hate

Lift: unreli, hate, dishonest, uneduc, uncar, selfish, greedi

Score: racist, selfish, ignor, bad, liar, greedi, bigot

Topic 7 Top Words:

Highest Prob: good, nice, like, great, peopl, cool, help

FREX: good, like, great, nice, cool, awesom, yes

Lift: yes, like, awesom, cool, great, good, nice

Score: good, nice, like, great, cool, help, kind

*Version 3:*

Topic 1 Top Words:

Highest Prob: good, trump, nice, like, great, cool, donald

FREX: good, like, cool, nice, donald, trump, great

Lift: donald, like, cool, good, nice, great, trump

Score: good, trump, like, nice, great, cool, donald

Topic 2 Top Words:

Highest Prob: conserv, religi, right, educ, pro, christian, class

FREX: pro, educ, religi, life, conserv, middl, class

Lift: fiscal, life, pro, frugal, middl, militari, older

Score: conserv, religi, pro, educ, right, middl, life

Topic 3 Top Words:

Highest Prob: right, support, self, idiot, conserv, liber, awesom

FREX: support, idiot, self, liber, right, awesom, negat

Lift: support, idiot, liber, self, negat, awesom, evil

Score: right, support, self, idiot, liber, negat, conserv

Topic 4 Top Words:

Highest Prob: rich, white, racist, conserv, old, mind, ignor

FREX: racist, old, bigot, close, rich, white, ignor

Lift: close, bigot, know, male, uneduc, racist, old

Score: rich, white, racist, old, ignor, mind, bigot

Topic 5 Top Words:

Highest Prob: smart, patriot, honest, american, strong, care, loyal

FREX: honest, patriot, smart, fair, intellig, american, loyal

Lift: god, leader, honest, intellig, fair, thrifti, patriot

Score: smart, patriot, honest, american, care, loyal, strong

Topic 6 Top Words:

Highest Prob: nonrespons, peopl, rude, opinion, republican, red, concern

FREX: nonrespons, peopl, rude, opinion, republican, red, concern

Lift: nonrespons, sure, brave, cold, dedic, differ, faith

Score: nonrespons, unfair, unreli, leader, thrifti, god, hungri

Topic 7 Top Words:

Highest Prob: selfish, liar, bad, greedi, dumb, money, angri

FREX: bad, greedi, liar, selfish, dishonest, mean, wrong

Lift: unreli, dishonest, wrong, bore, bad, mean, unfair

Score: selfish, liar, bad, greedi, mean, dishonest, money

*Version 5:*

Topic 1 Top Words:

Highest Prob: smart, patriot, right, honest, american, care, strong

FREX: patriot, honest, smart, american, care, freedom, work

Lift: god, freedom, honest, patriot, american, care, work

Score: smart, patriot, honest, right, american, care, strong

Topic 2 Top Words:

Highest Prob: liar, stupid, dumb, crazi, dishonest, peopl, angri

FREX: liar, dishonest, dumb, stupid, crazi, non, peopl

Lift: non, dishonest, close-mind, liar, dumb, stupid, aggress

Score: liar, stupid, dumb, crazi, dishonest, bore, peopl

Topic 3 Top Words:

Highest Prob: conserv, religi, educ, wealthi, pro, class, white

FREX: pro, educ, religi, conserv, life, middl, class

Lift: fiscal, life, pro, middl, frugal, older, rural

Score: conserv, religi, educ, pro, wealthi, middl, life

Topic 4 Top Words:

Highest Prob: good, bad, nice, like, great, cool, awesom

FREX: like, good, cool, nice, bad, great, awesom

Lift: yes, like, cool, awesom, good, great, nice

Score: good, bad, like, great, nice, cool, awesom

Topic 5 Top Words:

Highest Prob: selfish, trump, ignor, stubborn, money, rude, idiot

FREX: trump, selfish, rude, ignor, idiot, donald, know

Lift: hungri, donald, know, rude, trump, idiot, unreli

Score: selfish, trump, ignor, stubborn, money, rude, idiot

Topic 6 Top Words:

Highest Prob: nonrespons, dont, opinion, loud, republican, moral, uninform

FREX: nonrespons, dont, opinion, loud, republican, moral, uninform

Lift: nonrespons, sure, blue, cold, dedic, differ, dont

Score: nonrespons, realist, god, non, hungri, unreli, close-mind

Topic 7 Top Words:

Highest Prob: rich, white, racist, conserv, mind, old, bigot

FREX: rich, racist, bigot, white, close, mind, old

Lift: close, bigot, redneck, racist, rich, mind, narrow

Score: rich, racist, white, bigot, mind, close, old

**Eight topic models**

*Version 1:*

Topic 1 Top Words:

Highest Prob: nonrespons, opinion, wrong, red, moral, cold, poor

FREX: nonrespons, opinion, wrong, red, moral, cold, poor

Lift: nonrespons, sure, blue, cold, dedic, differ, faith

Score: nonrespons, logic, negat, yes, evil, fiscal, knowledg

Topic 2 Top Words:

Highest Prob: trump, ignor, money, anti, uneduc, loud, liber

FREX: trump, ignor, loud, money, donald, uneduc, anti

Lift: donald, trump, loud, uneduc, ignor, money, liber

Score: trump, ignor, money, uneduc, loud, donald, anti

Topic 3 Top Words:

Highest Prob: conserv, religi, wealthi, right, educ, pro, old

FREX: religi, conserv, pro, educ, wealthi, life, right

Lift: fiscal, life, pro, older, religi, educ, conserv

Score: conserv, religi, wealthi, pro, educ, life, old

Topic 4 Top Words:

Highest Prob: smart, honest, american, strong, care, loyal, work

FREX: honest, care, smart, loyal, intellig, american, help

Lift: intellig, fair, care, honest, loyal, knowledg, help

Score: smart, honest, american, strong, care, loyal, work

Topic 5 Top Words:

Highest Prob: rich, white, racist, conserv, bigot, old, tradit

FREX: rich, racist, white, bigot, old, male, tradit

Lift: bigot, racist, rich, white, male, hypocrit, sexist

Score: rich, white, racist, bigot, old, conserv, male

Topic 6 Top Words:

Highest Prob: selfish, mind, liar, stupid, greedi, close, dumb

FREX: stupid, selfish, greedi, dishonest, liar, mean, mind

Lift: know, dishonest, dont, narrow, stupid, negat, greedi

Score: selfish, liar, stupid, greedi, close, mind, mean

Topic 7 Top Words:

Highest Prob: patriot, conserv, independ, realist, less, valu, law

FREX: patriot, realist, independ, logic, less, law, conserv

Lift: logic, realist, patriot, law, independ, less, valu

Score: patriot, independ, realist, less, law, conserv, logic

Topic 8 Top Words:

Highest Prob: good, bad, nice, like, great, cool, support

FREX: like, good, bad, cool, nice, great, awesom

Lift: yes, like, cool, awesom, good, great, bad

Score: good, bad, like, great, nice, cool, awesom

*Version 5:*

Topic 1 Top Words:

Highest Prob: nonrespons, peopl, dont, opinion, liber, polit, republican

FREX: nonrespons, peopl, dont, opinion, liber, polit, republican

Lift: nonrespons, sure, know, cold, dedic, demand, differ

Score: nonrespons, owner, god, constitut, hypocrit, fiscal, awesom

Topic 2 Top Words:

Highest Prob: smart, patriot, honest, american, care, loyal, help

FREX: care, smart, honest, loyal, help, patriot, american

Lift: help, care, loyal, honest, open, smart, american

Score: smart, patriot, honest, american, care, loyal, help

Topic 3 Top Words:

Highest Prob: rich, white, wealthi, stubborn, conserv, male, bias

FREX: rich, white, male, stubborn, wealthi, bias, self

Lift: male, bias, rich, white, stubborn, wealthi, uncar

Score: rich, white, wealthi, stubborn, male, bias, conserv

Topic 4 Top Words:

Highest Prob: racist, selfish, trump, ignor, liar, mind, greedi

FREX: greedi, selfish, racist, liar, stupid, dumb, ignor

Lift: uneduc, dumb, greedi, hate, mean, stupid, hypocrit

Score: racist, selfish, trump, ignor, liar, greedi, stupid

Topic 5 Top Words:

Highest Prob: conserv, right, christian, pro, gun, tradit, independ

FREX: pro, life, rural, gun, christian, conserv, govern

Lift: life, rural, pro, constitut, frugal, govern, fiscal

Score: conserv, pro, christian, gun, life, right, rural

Topic 6 Top Words:

Highest Prob: educ, strong, class, busi, middl, hardwork, freedom

FREX: middl, educ, class, hardwork, freedom, strong, busi

Lift: middl, freedom, hardwork, owner, class, educ, moral

Score: educ, class, middl, strong, busi, hardwork, freedom

Topic 7 Top Words:

Highest Prob: religi, old, conserv, less, law, upper, collar

FREX: old, religi, less, law, upper, collar, brainwash

Lift: old, religi, law, less, brainwash, upper, confid

Score: religi, old, less, conserv, law, upper, collar

Topic 8 Top Words:

Highest Prob: good, bad, nice, like, great, cool, awesom

FREX: good, like, bad, cool, awesom, nice, great

Lift: like, cool, awesom, great, good, bad, nice

Score: good, bad, like, great, nice, cool, awesom

**Nine topic models**

*Version 5:*

Topic 1 Top Words:

Highest Prob: selfish, liar, bad, greedi, angri, crazi, dishonest

FREX: bad, liar, selfish, dishonest, angri, greedi, crazi

Lift: dishonest, uninform, evil, bad, liar, selfish, angri

Score: selfish, liar, bad, greedi, angri, dishonest, hate

Topic 2 Top Words:

Highest Prob: nonrespons, liber, bore, republican, moral, know, love

FREX: nonrespons, liber, bore, republican, moral, know, love

Lift: nonrespons, brave, cold, dedic, faith, know, negat

Score: nonrespons, collar, uninform, evil, donald, upper, awesom

Topic 3 Top Words:

Highest Prob: patriot, educ, tradit, independ, conserv, work, respons

FREX: patriot, independ, freedom, educ, respons, realist, tradit

Lift: freedom, realist, independ, less, respons, patriot, hardwork

Score: patriot, educ, independ, tradit, work, respons, hardwork

Topic 4 Top Words:

Highest Prob: good, trump, nice, support, like, great, peopl

FREX: like, good, great, nice, cool, donald, trump

Lift: like, donald, cool, awesom, great, good, nice

Score: good, trump, like, nice, great, support, cool

Topic 5 Top Words:

Highest Prob: rich, white, wealthi, old, class, money, stubborn

FREX: white, class, old, male, rich, wealthi, money

Lift: male, upper, collar, old, class, white, wealthi

Score: rich, white, wealthi, old, class, money, male

Topic 6 Top Words:

Highest Prob: stupid, dumb, mean, rude, idiot, narrow, interest

FREX: stupid, dumb, mean, rude, idiot, interest, narrow

Lift: dumb, stupid, mean, rude, idiot, interest, narrow

Score: stupid, dumb, mean, rude, idiot, interest, narrow

Topic 7 Top Words:

Highest Prob: conserv, religi, right, gun, pro, life, older

FREX: pro, conserv, life, gun, religi, older, right

Lift: life, pro, rural, older, gun, conserv, religi

Score: conserv, religi, pro, gun, right, life, older

Topic 8 Top Words:

Highest Prob: racist, mind, ignor, bigot, close, uneduc, dont

FREX: racist, bigot, close, ignor, mind, uneduc, dont

Lift: close, bigot, racist, ignor, uneduc, mind, sexist

Score: racist, ignor, mind, bigot, close, uneduc, dont

Topic 9 Top Words:

Highest Prob: smart, honest, american, strong, care, loyal, right

FREX: honest, loyal, smart, care, intellig, american, fair

Lift: loyal, intellig, care, fair, help, honest, smart

Score: smart, honest, american, strong, care, loyal, intellig

**Eleven topic models**

*Version 1:*

Topic 1 Top Words:

Highest Prob: support, idiot, arrog, bias, radic, respect, militari

FREX: support, idiot, arrog, bias, radic, respect, brave

Lift: support, idiot, bias, arrog, gop, brave, radic

Score: support, idiot, arrog, bias, trustworthi, radic, respect

Topic 2 Top Words:

Highest Prob: smart, right, care, peopl, work, fair, wing

FREX: smart, care, work, fair, right, wing, peopl

Lift: wing, fair, work, care, smart, peopl, right

Score: smart, right, care, peopl, work, fair, wing

Topic 3 Top Words:

Highest Prob: conserv, religi, pro, gun, class, busi, middl

FREX: pro, conserv, life, class, middl, gun, religi

Lift: life, pro, middl, rural, class, conserv, gun

Score: conserv, religi, pro, class, gun, busi, middl

Topic 4 Top Words:

Highest Prob: white, wealthi, ignor, bad, bigot, uneduc, male

FREX: white, wealthi, bigot, ignor, male, uneduc, bad

Lift: male, bigot, white, wealthi, uneduc, bad, ignor

Score: white, wealthi, ignor, bigot, bad, male, uneduc

Topic 5 Top Words:

Highest Prob: liar, educ, rude, uncar, less, liber, unreli

FREX: liar, educ, less, uncar, rude, liber, unreli

Lift: liar, less, liber, uncar, educ, rude, unreli

Score: liar, educ, rude, uncar, less, liber, unreli

Topic 6 Top Words:

Highest Prob: rich, selfish, old, greedi, dishonest, mean, hate

FREX: selfish, greedi, rich, dishonest, old, hate, mean

Lift: selfish, greedi, dishonest, hate, rich, old, mean

Score: rich, selfish, old, greedi, dishonest, hate, mean

Topic 7 Top Words:

Highest Prob: nonrespons, opinion, concern, yes, law, cold, negat

FREX: nonrespons, opinion, concern, law, cold, negat, bold

Lift: nonrespons, sure, cold, differ, yes, negat, weird

Score: nonrespons, sure, kind, donald, rural, uncar, less

Topic 8 Top Words:

Highest Prob: trump, crazi, angri, dont, donald, know, follow

FREX: trump, dont, donald, angri, crazi, know, non

Lift: donald, dont, trump, angri, crazi, know, non

Score: trump, crazi, angri, dont, donald, know, non

Topic 9 Top Words:

Highest Prob: racist, mind, stupid, close, stubborn, dumb, narrow

FREX: racist, close, stupid, mind, narrow, dumb, stubborn

Lift: close, narrow, racist, bore, dumb, stupid, mind

Score: racist, mind, stupid, close, dumb, stubborn, narrow

Topic 10 Top Words:

Highest Prob: patriot, honest, american, strong, loyal, independ, christian

FREX: patriot, honest, hardwork, american, independ, loyal, freedom

Lift: freedom, hardwork, patriot, honest, loyal, independ, american

Score: patriot, honest, american, strong, loyal, independ, hardwork

Topic 11 Top Words:

Highest Prob: good, nice, like, great, cool, awesom, interest

FREX: good, like, nice, great, cool, awesom, interest

Lift: like, cool, good, great, nice, awesom, interest

Score: good, nice, like, great, cool, strong, awesom

*Version 2:*

Topic 1 Top Words:

Highest Prob: greedi, dishonest, dont, know, liber, untrustworthi, corpor

FREX: dishonest, dont, greedi, know, untrustworthi, liber, fanat

Lift: dont, dishonest, greedi, know, fanat, untrustworthi, gop

Score: greedi, dishonest, dont, know, liber, untrustworthi, corpor

Topic 2 Top Words:

Highest Prob: racist, pro, support, life, arrog, hypocrit, red

FREX: racist, life, pro, arrog, support, hypocrit, red

Lift: life, racist, arrog, pro, support, homophob, hypocrit

Score: racist, pro, life, arrog, support, hypocrit, red

Topic 3 Top Words:

Highest Prob: smart, patriot, honest, care, loyal, independ, work

FREX: honest, smart, loyal, patriot, intellig, work, independ

Lift: intellig, honest, loyal, work, smart, independ, patriot

Score: smart, patriot, honest, loyal, independ, care, work

Topic 4 Top Words:

Highest Prob: right, strong, wing, conserv, militari, trust, patriot

FREX: right, wing, strong, militari, trust, conserv, patriot

Lift: wing, right, strong, militari, trust, bias, patriot

Score: right, strong, wing, conserv, patriot, militari, trust

Topic 5 Top Words:

Highest Prob: nonrespons, money, opinion, bore, wrong, idiot, love

FREX: nonrespons, money, opinion, bore, wrong, idiot, love

Lift: nonrespons, sure, cold, differ, individu, negat, practic

Score: nonrespons, sure, kind, awesom, uncar, male, trustworthi

Topic 6 Top Words:

Highest Prob: white, rich, old, educ, class, tradit, busi

FREX: class, old, white, middl, rich, busi, educ

Lift: male, middl, class, older, old, white, busi

Score: white, rich, old, educ, class, tradit, busi

Topic 7 Top Words:

Highest Prob: trump, mind, stupid, close, dumb, angri, narrow

FREX: trump, close, mind, stupid, narrow, angri, dumb

Lift: close, narrow, trump, stupid, angri, mind, dumb

Score: trump, mind, stupid, close, dumb, angri, narrow

Topic 8 Top Words:

Highest Prob: american, crazi, peopl, mean, power, proud, crook

FREX: crazi, peopl, american, power, mean, proud, crook

Lift: peopl, crazi, power, american, mean, proud, confid

Score: american, crazi, peopl, mean, power, proud, crook

Topic 9 Top Words:

Highest Prob: good, nice, like, great, cool, awesom, yes

FREX: good, like, cool, nice, great, awesom, yes

Lift: like, awesom, cool, good, great, nice, yes

Score: good, nice, like, great, cool, awesom, kind

Topic 10 Top Words:

Highest Prob: conserv, religi, wealthi, anti, govern, respons, gun

FREX: religi, conserv, wealthi, anti, govern, respons, money

Lift: religi, wealthi, conserv, govern, anti, orient, respons

Score: conserv, religi, wealthi, anti, govern, respons, pro

Topic 11 Top Words:

Highest Prob: selfish, liar, bad, ignor, hate, stubborn, rude

FREX: bad, selfish, liar, hate, uncar, ignor, rude

Lift: uncar, hate, bad, selfish, liar, rude, ignor

Score: selfish, bad, liar, hate, ignor, uncar, hard

*Version 3:*

Topic 1 Top Words:

Highest Prob: ignor, selfish, stupid, greedi, crazi, dumb, power

FREX: stupid, ignor, greedi, crazi, selfish, dumb, evil

Lift: stupid, greedi, crazi, ignor, dumb, evil, fanat

Score: ignor, stupid, greedi, selfish, crazi, dumb, power

Topic 2 Top Words:

Highest Prob: right, old, support, wing, idiot, mean, conserv

FREX: right, old, wing, support, idiot, mean, parti

Lift: wing, right, old, support, idiot, fashion, parti

Score: right, old, support, wing, idiot, mean, parti

Topic 3 Top Words:

Highest Prob: nonrespons, dont, liber, bore, republican, concern, moral

FREX: nonrespons, dont, liber, bore, republican, concern, moral

Lift: nonrespons, sure, know, blue, bold, cold, dedic

Score: nonrespons, sure, know, great, dedic, rural, weird

Topic 4 Top Words:

Highest Prob: racist, good, bad, close, liar, like, mind

FREX: bad, racist, close, good, like, liar, nice

Lift: like, bad, close, racist, good, nice, homophob

Score: racist, good, bad, close, like, nice, great

Topic 5 Top Words:

Highest Prob: smart, patriot, honest, american, strong, care, loyal

FREX: honest, patriot, smart, american, loyal, strong, intellig

Lift: honest, loyal, intellig, patriot, american, smart, work

Score: smart, patriot, honest, american, strong, care, loyal

Topic 6 Top Words:

Highest Prob: trump, stubborn, rude, help, opinion, nice, wrong

FREX: trump, help, rude, opinion, stubborn, wrong, poor

Lift: trump, opinion, rude, help, stubborn, poor, differ

Score: trump, stubborn, rude, help, opinion, nice, wrong

Topic 7 Top Words:

Highest Prob: conserv, wealthi, white, religi, christian, male, rural

FREX: wealthi, conserv, rural, male, christian, religi, white

Lift: rural, wealthi, male, conserv, evangel, christian, big

Score: conserv, wealthi, white, religi, christian, male, rural

Topic 8 Top Words:

Highest Prob: educ, tradit, religi, conserv, respons, freedom, less

FREX: educ, tradit, respons, religi, freedom, less, fiscal

Lift: respons, freedom, educ, tradit, fiscal, success, less

Score: educ, tradit, religi, respons, freedom, conserv, less

Topic 9 Top Words:

Highest Prob: money, angri, self, hate, bias, hard, cool

FREX: angri, money, hate, bias, self, hard, cool

Lift: angri, hate, bias, money, self, uninform, sad

Score: angri, money, self, hate, bias, hard, cool

Topic 10 Top Words:

Highest Prob: gun, bigot, pro, class, busi, peopl, anti

FREX: pro, gun, class, bigot, middl, life, anti

Lift: life, middl, pro, anti, class, busi, gun

Score: gun, pro, class, bigot, busi, peopl, anti

Topic 11 Top Words:

Highest Prob: rich, white, selfish, arrog, uncar, close-mind, mind

FREX: rich, white, arrog, selfish, uncar, close-mind, moron

Lift: rich, arrog, uncar, white, close-mind, moron, selfish

Score: rich, white, selfish, arrog, uncar, close-mind, moron

**Reference not cited in main text**

Berinsky, Adam J., Michele F. Margolis, and Michael W. Sances. 2014. “Separating the Shirkers from the Workers? Making Sure Respondents Pay Attention on Self-Administered Surveys.” *American Journal of Political Science* 58(3): 739-753.

1. Political interest was asked with this question in both surveys: “Some people seem to follow what's going on in government and public affairs most of the time, whether there's an election going on or not. Others aren't that interested. Where you would place yourself on a scale from (1) you rarely follow what’s going on in government to (7) you follow what's going on in government and public affairs almost all of the time?” Respondents were then shown the numbers 1 through 7, with labels placed on 1 and 7 as described in the question stem. [↑](#footnote-ref-0)
2. Political knowledge was asked with the same battery of four questions in both surveys. The first asked “Do you happen to know which party currently has the most members in the House of Representatives in Washington, D.C.?” (Republicans, Democrats, Tie, Don’t know). The second asked “How much of a majority is required for the U.S. Senate and House to override a Presidential veto?” (Senate and House cannot override veto, ⅓, ⅔, ¾, Don’t know). The third asked “Whose responsibility is it to determine if a law is constitutional?” (President, Congress, Supreme Court, Don’t know). The fourth asked “Who is the current U.S. Secretary of State?” (Open-ended). For all four, don’t know and blank responses were coding as incorrect. Looking only at the more general political knowledge questions (about vetoes and constitutionality) creates an average of 1.4 out of 2 in 2016 and 1.1 out of 2 in 2021. [↑](#footnote-ref-1)
3. We did not use the stereotype questions themselves for two reasons. First, the Secretary of State question is unrelated to our research question, so it provides a way to assess response quality that is independent of responses that form the main part of our analysis. Second, the stereotype questions are sufficiently open-ended that it is less clear whether responses are non-sequiturs. For example, “good” is obviously non-responsive to the question “Who is the current Secretary of State,” but could easily be a sincere response to the prompt to “list four words that typically describe people who support <Democrats/Republicans>.” [↑](#footnote-ref-2)
4. Available at https://osf.io/nyv6e/?view\_only=120157aac70d49268fa038d2fdd8720e [↑](#footnote-ref-3)