Supplemental Materials for: Partisan polarization is the primary psychological motivation behind political fake news sharing on Twitter

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1. Survey

1a. Invitation letter

Hi there!

Aarhus University is carrying out some research to better understand people's motivations to share links, news and information on social media platforms, and they'd like your help.

If you'd like to participate, you just need to answer some questions about you, your media habits, and your opinions on a number of social and political issues, and then provide your Twitter handle at the end of this survey. Aarhus University would then combine your responses with your publicly available Twitter data. If you choose to participate, it's therefore important that your Twitter account is set to public and not to private. (If you haven't changed anything in the settings, it is automatically set to public.) Our hope is that the combination of survey data on social and political opinions and data from Twitter accounts will allow us to better understand the dynamics of social media: How, why, and with whom people interact in today's social media landscape. We'll remind you again of the objectives of this project, and what it means to be involved, at the end of this survey so you have all the information you need to make an informed decision about whether you want to participate.
Single

[**Intro**] If you are not interested in taking part in this project please click 'No Thanks' below, and you will be re-directed to another survey. You can also choose not to take part at the end of this survey.

1. Yes, I would like to continue the survey
2. No Thanks

1b. Link to consent form

Link

1c. Survey Questions: Operationalizations

Survey measures used to operationalize predictors from the ignorance theory:

`Age`: Age in years

- 1 = 18-22; 2 = 23-27; 3 = 28-32; 4 = 33-37; 5 = 38-42; 6 = 43-47; 7 = 48-52; 8 = 53-57; 8 = 58-62; 9 = 63-67; 10 = 68-72; 11 = 73-77; 12 = 78-82; 13 = 83+

`Cognitive Reflection Test(CRT-2)`: Number of correct answers

- If you're running a race and you pass the person in second place, what place are you in? [2]
- A farmer had 15 sheep and all but 8 died. How many are left? [8]
- Emily's father has three daughters. The first two are named April and May. What is the third daughter's name? [Emily]
- How many cubic feet of dirt are there in a hole that is 3' deep x 3' wide x 3' long? [0]

`Political Knowledge`: Number of correct answers

- Whose responsibility is it to determine if a law is constitutional or not – is it the President, the Congress, or the Supreme Court? [Supreme Court]
- How much of a majority is required for the U.S. Senate and House to override a presidential veto? [2/3 majority]
- Do you happen to know which party had the most members in the House of Representatives in Washington prior to the 2016 elections? [Republicans]
- Would you say that one of the major parties is more conservative than the other at the national level? If so, which party is more conservative? [Republicans]
- How many members of the U.S. Supreme Court are there? [9 members]

`Political Digital Media Literacy`: How often do you do the following (1: Never; 7: Several times a day)

- Sign an online petition.

- Email a national, state, or local government official about an issue of personal importance.
- Start or join a political group or group supporting a cause on a social networking site.
- Contribute money on the Internet for a political or social cause.
- Use the Internet to participate in volunteer activities related to a political or social campaign.
- Like or follow a page of a political group, party or candidate on social media.
- Post online personal views related to politics or campaigning.
- Comment on others' online posts about a political or social cause (including online news articles).
- Share someone else's political post to other people online.
- Like or favorite a post or message from a political group, party or candidate.

Survey measures used to operationalize predictors from the disruption theory:

`Trolling behavior`: 1=Strongly Disagree; 7=Strongly Agree

- I have sent people to shock websites for the lulz.
- I like to troll people in forums or the comments section of websites.
- I enjoy griefing other players in multiplayer games.
- The more beautiful and pure a thing is, the more satisfying it is to corrupt.

`Political cyniscism`: 1=Strongly Disagree; 7=Strongly Agree

- In Washington only back room politics are conducted
- Politics in the Unites States is sick
- They are using our tax money well in Washington
- Politics in the United States does consider the interest of the people
- The democracy in the United States function well
- Washington is perfectly able to solve problems in our society
- The democracy in the United States does not protect our rights

- The world of American politics does not know what citizens want

Survey measures used to operationalize predictors from the polarization theory:

`Partisanship`: "Generally speaking, do you usually think of yourself as a..."

- Strong Republican (=1), Not very strong Reupblican (=2), Closer to the Republican party (=3), Independent (=4), Closer to the Democratic party (=5), Not very strong Democrat (=6), Strong Democrat (=7)

`Feelings towards Democrats [/Republicans] (affect_dem; affect_rep)`: "What do you feel when you think about Democrats [/Republicans]?" 1=Not at all; 7=Very strongly

- Angry
- Frustrated
- Afraid
- Hopeful
- Enthusiastic
- Proud

2. Basic Descriptives

2a. Sample characteristics

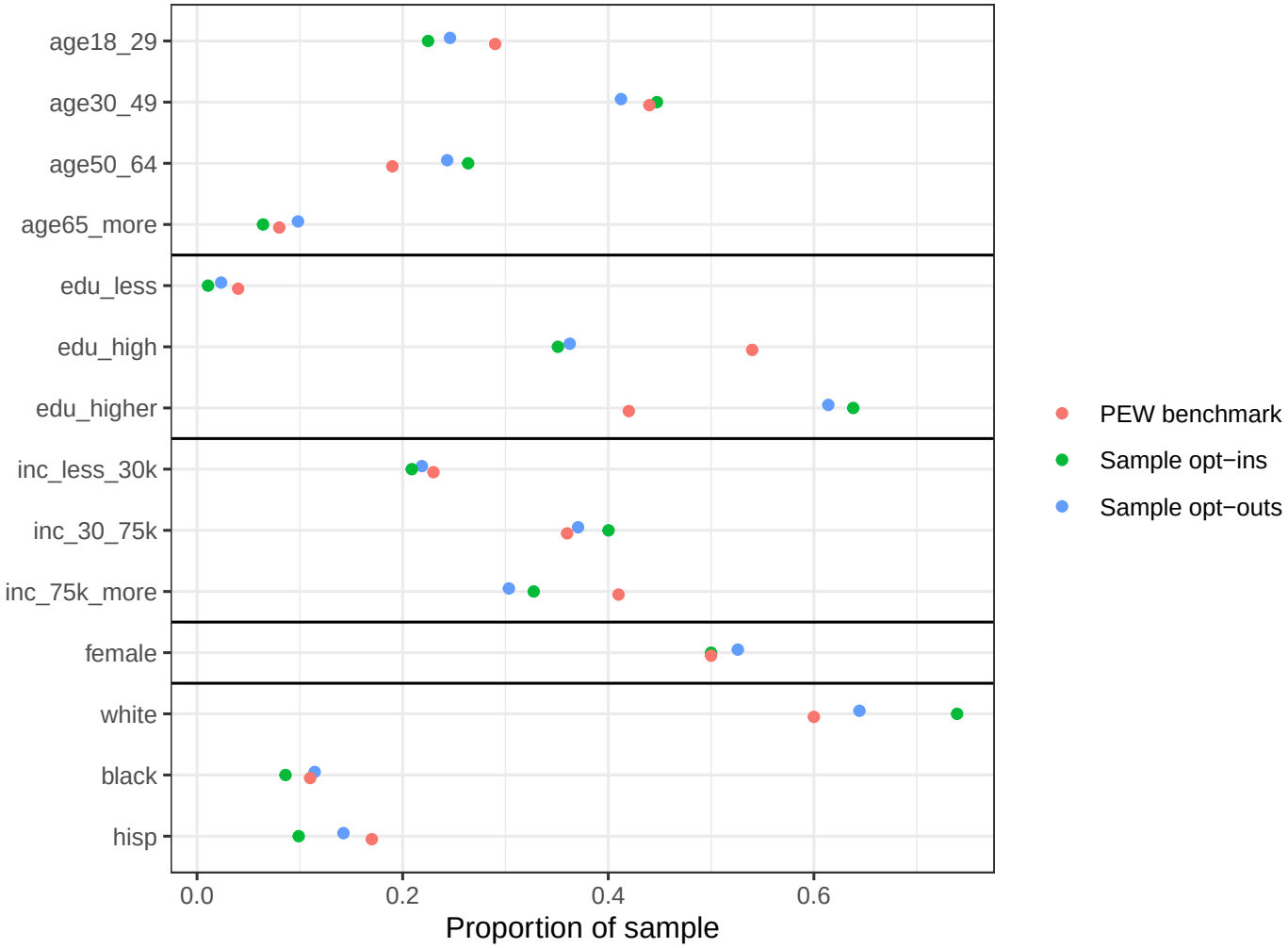


Figure SM 2a. Comparison of participant characteristics in our final sample (green dots) versus participant characteristics among people who accepted to participate in the survey but failed to provide their Twitter handle (blue dots) versus participant characteristics in PEW Twitter study (red dots).

2b. Independent & dependent variables

Table SM2a. Descriptions of main independent variables before standardization.

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
age	2,180	5.539	2.890	1	3	8	14
cognitive reflection	2,180	2.013	1.209	0	1	3	4
pol knowledge	2,180	3.829	1.418	0	3	5	5
pol digital literacy	2,180	2.429	1.097	1.000	1.600	3.000	7.000
trolling	2,180	1.676	1.199	1.000	1.000	1.750	7.000
cynicism	2,180	4.833	1.018	1.000	4.125	5.625	7.000
partisanship	2,180	3.211	2.158	1	1	5	7
affect_democrat	2,180	4.217	1.721	1.000	2.833	5.667	7.000
affect_republican	2,180	2.800	1.742	1.000	1.167	4.000	7.000

Table SM2b. Descriptions of main dependent variables.

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
fakeNews-total	2,180	1.500	17.562	0	0	0	513
fakeNews-dem	2,180	0.121	1.256	0	0	0	32
fakeNews-rep	2,180	1.176	16.460	0	0	0	510
realNews-total	2,180	35.963	137.865	0	0	16.2	2,321
realNews-dem	2,180	8.802	46.054	0	0	3	1,239
realNews-leanDem	2,180	12.475	57.139	0	0	6	1,672
realNews-center	2,180	7.309	39.510	0	0	3	1,063
realNews-leanRep	2,180	2.185	17.355	0	0	0	417
realNews-rep	2,180	5.191	56.251	0	0	0	1,758
fakeNews-total-dummy	2,180	0.106	0.308	0	0	0	1
fakeNews-dem-dummy	2,180	0.033	0.179	0	0	0	1
fakeNews-rep-dummy	2,180	0.061	0.240	0	0	0	1
realNews-total-dummy	2,180	0.586	0.493	0	0	1	1
realNews-dem-dummy	2,180	0.408	0.492	0	0	1	1
realNews-leanDem-dummy	2,180	0.496	0.500	0	0	1	1
realNews-center-dummy	2,180	0.404	0.491	0	0	1	1
realNews-leanRep-dummy	2,180	0.189	0.392	0	0	0	1
realNews-rep-dummy	2,180	0.197	0.398	0	0	0	1

Note. Variables with *dummy* suffix give the proportion of participants who shared at least one news story from a given news source.

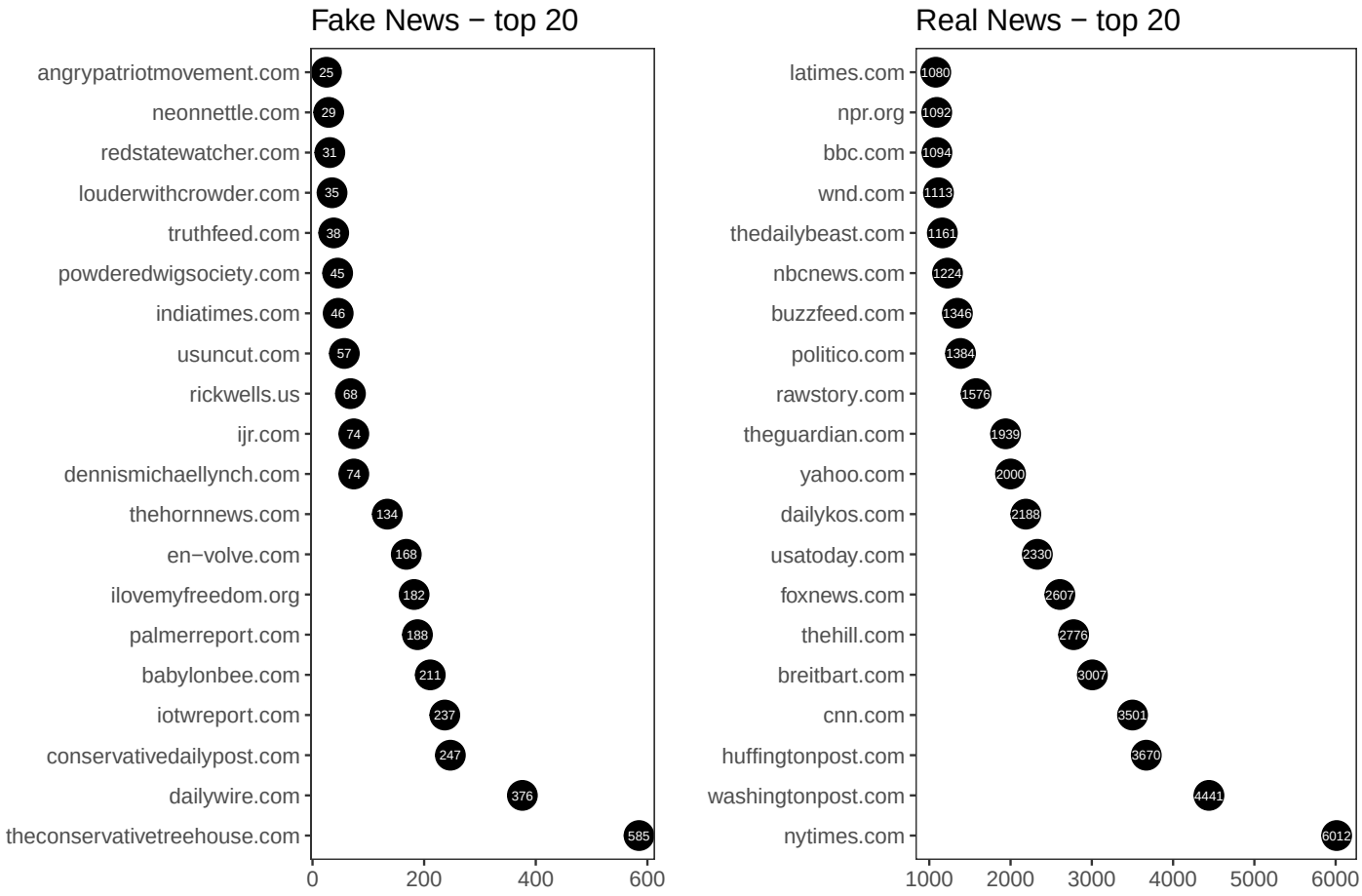


Figure SM 2b. Most popular fake news (left panel) and real news (right panel) web domains. Numbers in dots indicate number of times stories were shared by panelists.

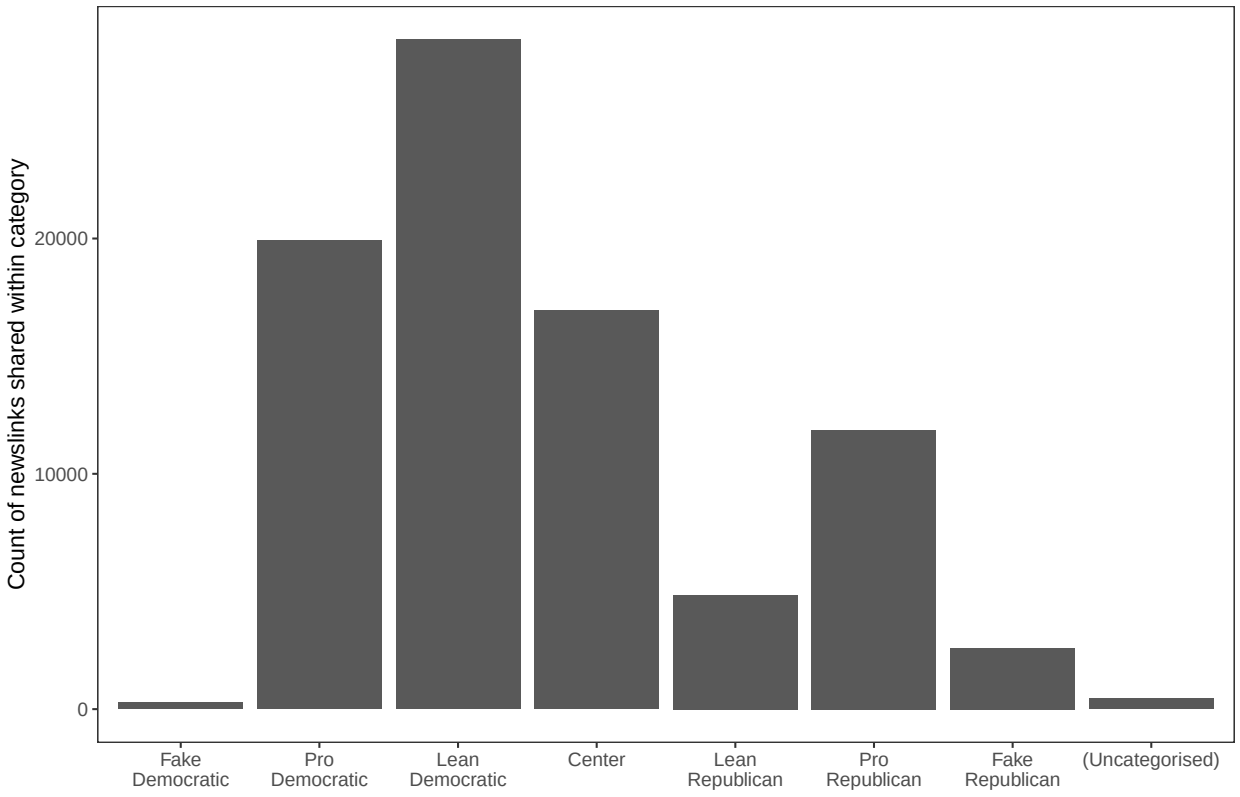


Figure SM 2c. Distribution of number of news links shared from different news sources. The figure shows the number of news stories shared from *pro*-Democratic fake news sources ($N_{\text{Fake Democratic}} = 271$), *pro*-Democratic real news sources ($N_{\text{Strong Democratic}} = 19{,}925$), real news sources that "lean Democratic" ($N_{\text{Lean Democratic}} = 28{,}452$), centrist news sources ($N_{\text{Center}} = 16{,}926$), real news sources that "lean Republican" ($N_{\text{Lean Republican}} = 4{,}850$), *pro*-Republican real news sources ($N_{\text{Strong Republican}} = 11{,}866$) and *pro*-Republican fake news sources ($N_{\text{Fake Republican}} = 2{,}595$).

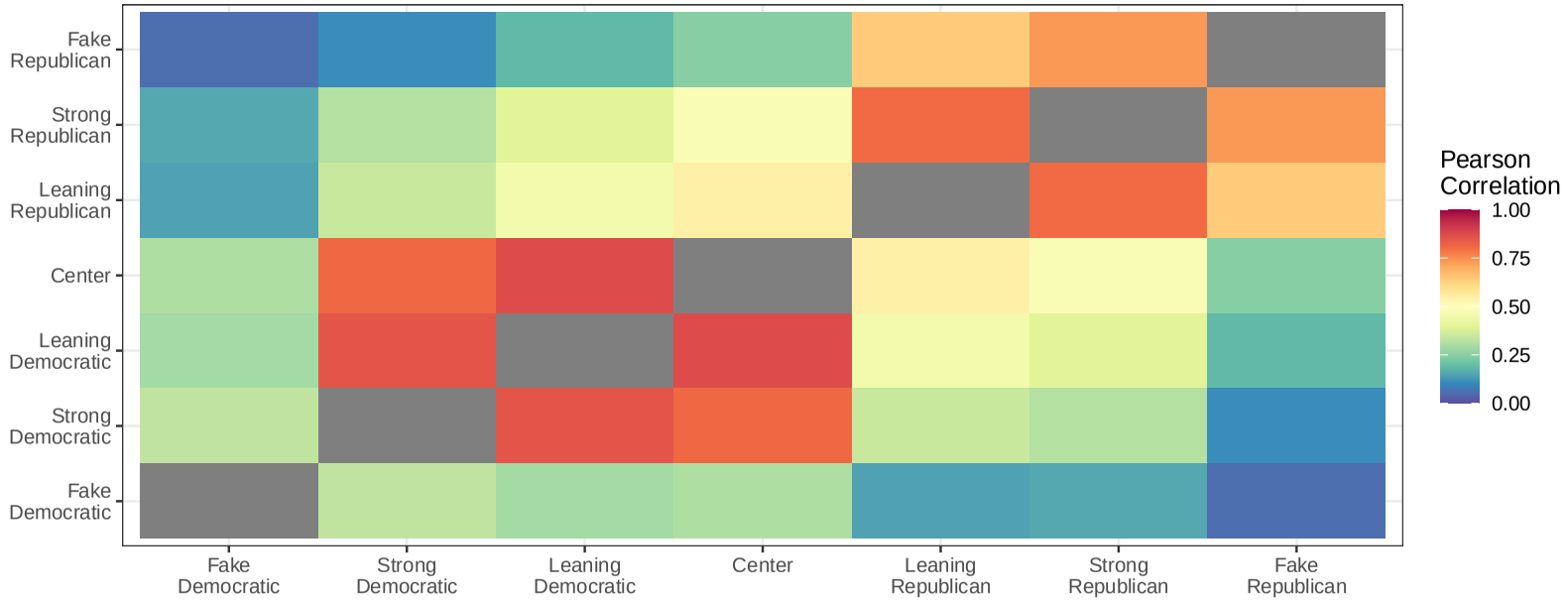


Figure SM 2d Correlations between sharing news from seven types of sources without excluding participants who have not shared a piece of news from any category.

3. Model Specifications (Figure 2 in main text)

In the main text analysis of Figure 2, we present results using Average Marginal Effects (AME) obtained from logistic regression models. We presented results using AMEs as logistic regression coefficients on the log-odds scale are notoriously difficult to interpret. Unlike coefficients on the log-odds scale, AMEs offer an intuitive understanding of the association between a dependent variable and a key predictor: They give the difference in the probability that the outcome equals 1 when the predictor of interest changes a certain amount (in our case: when the main predictors change from their minimum to their maximum value), averaged across the observed values of all other covariates in the model for all n data points.

Still, for the sake of full transparency, the figure and the tables in this section present logistic regression coefficients on the log-odds scale from the models used to construct Figure 2.

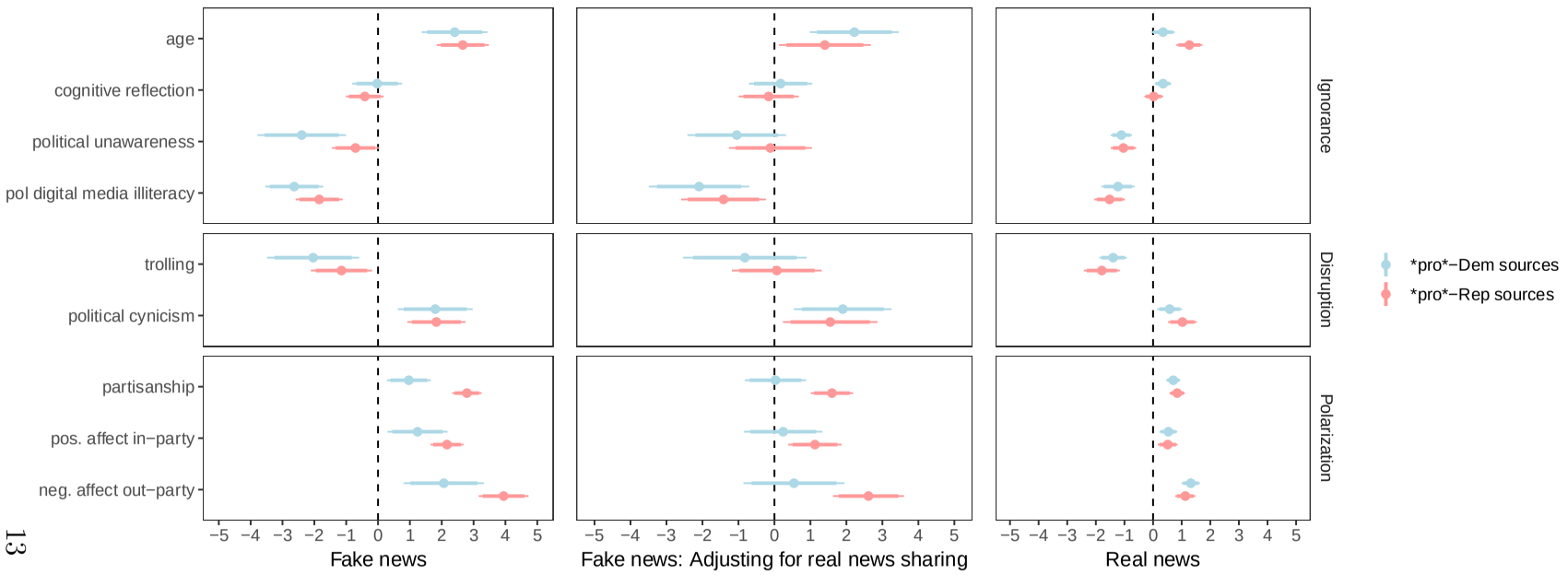


Figure SM 3a Logistic Regression Models with coefficients on log-odds scale. Horizontal bands represent 90% and 95% confidence intervals **Left**: Links to fake news sources. **Middle**: Links to fake news sources, controlling for (logged) real news sharing. **Right**: Links to real news sources. ***pro*-Dem sources**: *pro*-Democratic news publishers only. ***pro*-Rep sources**: *pro*-Republican news publishers only. **partisanship**: High values indicate participant identifies with political party supported by news source. **pos. affect in-party**: High values indicate positive feelings towards political party supported by news source. **neg. affect in-party**: High values indicate negative feelings towards political party opposed by news source. All independent variables range from 0 to 1. All models control for gender, race, education, income, political interest.

	Dependent variable:					
	pro-Dem Fake		*pro*-Dem Real	*pro*-Rep Fake		*pro*-Rep Real
	(1)	(2)	(3)	(4)	(5)	(6)
Age	2.406***	2.222***	0.350*	2.659***	1.402**	1.270***
	(0.561)	(0.614)	(0.207)	(0.425)	(0.583)	(0.231)
female	0.239	0.115	0.055	−0.391**	−0.155	−0.146
	(0.246)	(0.268)	(0.090)	(0.189)	(0.250)	(0.102)
white	−0.252	−0.417	0.260**	−0.169	−0.323	0.176
	(0.289)	(0.320)	(0.103)	(0.219)	(0.296)	(0.123)
income	−0.0004	−0.005	0.003	0.003	−0.005	0.004*
	(0.006)	(0.006)	(0.002)	(0.004)	(0.006)	(0.002)
highered	−0.048	−0.218	0.195**	−0.441**	−0.637**	−0.051
	(0.265)	(0.289)	(0.094)	(0.191)	(0.255)	(0.108)
partysource						
interest	0.661***	0.247	0.303***	0.278***	0.186	0.307***
	(0.178)	(0.184)	(0.044)	(0.108)	(0.139)	(0.055)
share_real_news_log		0.837***			1.471***	
		(0.079)			(0.099)	
Constant	−7.143***	−7.069***	−1.546***	−4.459***	−4.947***	−2.868***
	(0.856)	(0.885)	(0.201)	(0.502)	(0.670)	(0.257)
Observations	2,180	2,180	2,180	2,180	2,180	2,180

Table SM3a. Association Between Age and News Sharing. Logistic regression coefficients (log-odds scale) with standard errors in parentheses. Dependent variables: Dummy variables, 0 = Participants did not share story from news domain; 1 = Participant shared 1+ story from news domain. Covariates: gender (`female`), ethnicity (`white`), income level (`income`), educational level (`highered`), political interest (`interest`), logged number of real news shared (`share_real_news_log`) *p<0.1; **p<0.05; ***p<0.01

	Dependent variable:					
	pro-Dem Fake		*pro*-Dem Real	*pro*-Rep Fake		*pro*-Rep Real
	(1)	(2)	(3)	(4)	(5)	(6)
Cognitive Reflection	−0.029	0.173	0.349**	−0.415	−0.161	0.023
	(0.408)	(0.442)	(0.148)	(0.302)	(0.418)	(0.168)
female	0.235	0.162	0.063	−0.416**	−0.175	−0.162
	(0.245)	(0.264)	(0.090)	(0.188)	(0.250)	(0.102)
white	−0.109	−0.397	0.251**	0.030	−0.237	0.252**
	(0.288)	(0.317)	(0.103)	(0.216)	(0.293)	(0.122)
income	0.001	−0.005	0.003	0.005	−0.005	0.004*
	(0.005)	(0.006)	(0.002)	(0.004)	(0.006)	(0.002)
highered	−0.023	−0.231	0.182*	−0.378**	−0.645**	−0.035
	(0.263)	(0.285)	(0.094)	(0.188)	(0.255)	(0.108)
partysource						
interest	0.766***	0.327*	0.319***	0.394***	0.223	0.362***
	(0.174)	(0.180)	(0.043)	(0.104)	(0.136)	(0.053)
share_real_news_log		0.852***			1.504***	
		(0.079)			(0.098)	
Constant	−6.725***	−6.648***	−1.652***	−3.841***	−4.539***	−2.702***
	(0.856)	(0.882)	(0.209)	(0.499)	(0.661)	(0.263)
Observations	2,180	2,180	2,180	2,180	2,180	2,180

Table SM3b. Association Between Cognitive Reflection and News Sharing. Logistic regression coefficients (log-odds scale) with standard errors in parentheses. Dependent variables: Dummy variables, 0 = Participants did not share story from news domain; 1 = Participant shared 1+ story from news domain. Covariates: gender (`female`), ethnicity (`white`), income level (`income`), educational level (`highered`), political interest (`interest`), logged number of real news shared (`share_real_news_log`) *p<0.1; **p<0.05; ***p<0.01

	Dependent variable:					
	pro-Dem Fake		*pro*-Dem Real	*pro*-Rep Fake		*pro*-Rep Real
	(1)	(2)	(3)	(4)	(5)	(6)
Political Knowledge	−2.395***	−1.048	−1.107***	−0.708	−0.112	−1.035***
	(0.775)	(0.788)	(0.187)	(0.434)	(0.590)	(0.236)
female	0.373	0.234	0.133	−0.344*	−0.158	−0.089
	(0.247)	(0.269)	(0.092)	(0.189)	(0.255)	(0.103)
white	−0.314	−0.439	0.140	−0.087	−0.260	0.131
	(0.291)	(0.317)	(0.105)	(0.220)	(0.296)	(0.125)
income	0.001	−0.005	0.003	0.004	−0.005	0.004*
	(0.006)	(0.006)	(0.002)	(0.004)	(0.006)	(0.002)
highered	−0.154	−0.273	0.119	−0.436**	−0.657***	−0.105
	(0.264)	(0.286)	(0.095)	(0.189)	(0.255)	(0.109)
partysource						
interest	0.573***	0.230	0.210***	0.325***	0.212	0.264***
	(0.183)	(0.193)	(0.046)	(0.112)	(0.146)	(0.058)
share_real_news_log		0.835***			1.502***	
		(0.080)			(0.099)	
Constant	−5.362***	−5.908***	−0.688***	−3.517***	−4.532***	−1.971***
	(0.913)	(0.969)	(0.241)	(0.564)	(0.744)	(0.297)
Observations	2,180	2,180	2,180	2,180	2,180	2,180

Table SM3c. Association Between Political Knowledge and News Sharing. Logistic regression coefficients (log-odds scale) with standard errors in parentheses. Dependent variables: Dummy variables, 0 = Participants did not share story from news domain; 1 = Participant shared 1+ story from news domain. Covariates: gender (`female`), ethnicity (`white`), income level (`income`), educational level (`highered`), political interest (`interest`), logged number of real news shared (`share_real_news_log`) *p<0.1; **p<0.05; ***p<0.01

	Dependent variable:					
	pro-Dem Fake		*pro*-Dem Real	*pro*-Rep Fake		*pro*-Rep Real
	(1)	(2)	(3)	(4)	(5)	(6)
Digital Media Literacy	−2.633***	−2.095***	−1.226***	−1.847***	−1.415**	−1.519***
	(0.570)	(0.735)	(0.270)	(0.454)	(0.697)	(0.281)
female	0.198	0.088	0.037	−0.422**	−0.209	−0.184*
	(0.246)	(0.266)	(0.090)	(0.188)	(0.250)	(0.102)
white	0.026	−0.346	0.319***	0.071	−0.236	0.309**
	(0.292)	(0.317)	(0.103)	(0.217)	(0.290)	(0.123)
income	0.002	−0.005	0.003	0.004	−0.005	0.004**
	(0.005)	(0.006)	(0.002)	(0.004)	(0.006)	(0.002)
highered	−0.080	−0.227	0.182*	−0.431**	−0.662***	−0.058
	(0.265)	(0.286)	(0.094)	(0.189)	(0.254)	(0.108)
partysource						
interest	0.550***	0.150	0.240***	0.259**	0.110	0.258***
	(0.176)	(0.189)	(0.046)	(0.108)	(0.146)	(0.056)
share_real_news_log		0.827***			1.493***	
		(0.079)			(0.099)	
Constant	−4.007***	−4.281***	−0.262	−2.131***	−3.088***	−1.150***
	(0.987)	(1.140)	(0.337)	(0.656)	(0.966)	(0.376)
Observations	2,180	2,180	2,180	2,180	2,180	2,180

Table SM3d. Association Between Digital Media Literacy and News Sharing. Logistic regression coefficients (log-odds scale) with standard errors in parentheses. Dependent variables: Dummy variables, 0 = Participants did not share story from news domain; 1 = Participant shared 1+ story from news domain. Covariates: gender (`female`), ethnicity (`white`), income level (`income`), educational level (`highered`), political interest (`interest`), logged number of real news shared (`share_real_news_log`) *p<0.1; **p<0.05; ***p<0.01

	Dependent variable:					
	pro-Dem Fake		*pro*-Dem Real	*pro*-Rep Fake		*pro*-Rep Real
	(1)	(2)	(3)	(4)	(5)	(6)
Trolling	−2.039**	−0.822	−1.396***	−1.149*	0.067	−1.791***
	(1.022)	(1.107)	(0.242)	(0.603)	(0.798)	(0.347)
female	0.158	0.137	−0.027	−0.447**	−0.165	−0.246**
	(0.246)	(0.266)	(0.091)	(0.189)	(0.252)	(0.103)
white	−0.253	−0.416	0.135	−0.104	−0.246	0.099
	(0.290)	(0.317)	(0.106)	(0.219)	(0.296)	(0.125)
income	0.001	−0.005	0.002	0.004	−0.005	0.004
	(0.005)	(0.006)	(0.002)	(0.004)	(0.006)	(0.002)
highered	−0.022	−0.217	0.208**	−0.391**	−0.653**	−0.032
	(0.263)	(0.284)	(0.094)	(0.188)	(0.254)	(0.108)
partysource						
interest	0.738***	0.312*	0.300***	0.375***	0.222	0.339***
	(0.174)	(0.181)	(0.043)	(0.104)	(0.137)	(0.054)
share_real_news_log		0.844***			1.505***	
		(0.079)			(0.099)	
Constant	−6.298***	−6.389***	−1.124***	−3.724***	−4.619***	−2.266***
	(0.852)	(0.882)	(0.209)	(0.502)	(0.666)	(0.263)
Observations	2,180	2,180	2,180	2,180	2,180	2,180

Table SM3e. Association Between Trolling and News Sharing. Logistic regression coefficients (log-odds scale) with standard errors in parentheses. Dependent variables: Dummy variables, 0 = Participants did not share story from news domain; 1 = Participant shared 1+ story from news domain. Covariates: gender (`female`), ethnicity (`white`), income level (`income`), educational level (`highered`), political interest (`interest`), logged number of real news shared (`share_real_news_log`) *p<0.1; **p<0.05; ***p<0.01

	Dependent variable:					
	pro-Dem Fake		*pro*-Dem Real	*pro*-Rep Fake		*pro*-Rep Real
	(1)	(2)	(3)	(4)	(5)	(6)
Political Cynicism	1.797***	1.898***	0.580***	1.830***	1.550**	1.025***
	(0.618)	(0.677)	(0.219)	(0.459)	(0.610)	(0.251)
female	0.195	0.073	0.037	−0.434**	−0.214	−0.183*
	(0.245)	(0.268)	(0.090)	(0.188)	(0.251)	(0.102)
white	−0.145	−0.358	0.262**	−0.055	−0.272	0.222*
	(0.287)	(0.318)	(0.102)	(0.216)	(0.294)	(0.122)
income	0.001	−0.005	0.003	0.004	−0.005	0.004*
	(0.005)	(0.006)	(0.002)	(0.004)	(0.006)	(0.002)
highered	0.063	−0.157	0.219**	−0.316*	−0.610**	0.005
	(0.265)	(0.287)	(0.094)	(0.189)	(0.255)	(0.108)
partysource						
interest	0.736***	0.310*	0.312***	0.367***	0.215	0.350***
	(0.174)	(0.180)	(0.043)	(0.104)	(0.137)	(0.054)
share_real_news_log		0.856***			1.499***	
		(0.080)			(0.099)	
Constant	−8.423***	−8.442***	−2.027***	−5.728***	−6.124***	−3.636***
	(1.035)	(1.111)	(0.282)	(0.664)	(0.898)	(0.347)
Observations	2,180	2,180	2,180	2,180	2,180	2,180

Table SM3f. Association Between Political Cynicism and News Sharing. Logistic regression coefficients (log-odds scale) with standard errors in parentheses. Dependent variables: Dummy variables, 0 = Participants did not share story from news domain; 1 = Participant shared 1+ story from news domain. Covariates: gender (`female`), ethnicity (`white`), income level (`income`), educational level (`highered`), political interest (`interest`), logged number of real news shared (`share_real_news_log`) *p<0.1; **p<0.05; ***p<0.01

	Dependent variable:					
	pro-Dem Fake		*pro*-Dem Real	*pro*-Rep Fake		*pro*-Rep Real
	(1)	(2)	(3)	(4)	(5)	(6)
Partisanship	0.967**	0.028	0.708***	2.790***	1.598***	0.844***
	(0.392)	(0.443)	(0.126)	(0.272)	(0.352)	(0.138)
female	0.139	0.155	−0.025	−0.178	−0.001	−0.078
	(0.247)	(0.269)	(0.091)	(0.196)	(0.256)	(0.103)
white	−0.075	−0.380	0.342***	−0.170	−0.369	0.202*
	(0.288)	(0.314)	(0.103)	(0.224)	(0.298)	(0.123)
income	0.002	−0.005	0.003	0.004	−0.005	0.004*
	(0.005)	(0.006)	(0.002)	(0.004)	(0.006)	(0.002)
highered	−0.061	−0.225	0.181*	−0.345*	−0.648**	−0.005
	(0.264)	(0.284)	(0.094)	(0.196)	(0.259)	(0.108)
partysource						
interest	0.710***	0.325*	0.286***	0.531***	0.336**	0.413***
	(0.174)	(0.183)	(0.043)	(0.109)	(0.141)	(0.055)
share_real_news_log		0.849***			1.386***	
		(0.080)			(0.101)	
Constant	−7.139***	−6.575***	−1.817***	−6.046***	−5.732***	−3.250***
	(0.850)	(0.864)	(0.208)	(0.562)	(0.712)	(0.275)
Observations	2,180	2,180	2,180	2,180	2,180	2,180

Table SM3g. Association Between Partisanship and News Sharing. Logistic regression coefficients (log-odds scale) with standard errors in parentheses. Dependent variables: Dummy variables, 0 = Participants did not share story from news domain; 1 = Participant shared 1+ story from news domain. Covariates: gender (`female`), ethnicity (`white`), income level (`income`), educational level (`highered`), political interest (`interest`), logged number of real news shared (`share_real_news_log`) *p<0.1; **p<0.05; ***p<0.01

	Dependent variable:					
	pro-Dem Fake		*pro*-Dem Real	*pro*-Rep Fake		*pro*-Rep Real
	(1)	(2)	(3)	(4)	(5)	(6)
Pos. Affect In-Party	1.239***	0.243	0.537***	2.165***	1.125***	0.512***
	(0.450)	(0.504)	(0.156)	(0.287)	(0.406)	(0.173)
female	0.162	0.149	0.014	−0.342*	−0.116	−0.141
	(0.246)	(0.265)	(0.090)	(0.191)	(0.252)	(0.102)
white	−0.060	−0.381	0.325***	0.117	−0.233	0.277**
	(0.288)	(0.314)	(0.103)	(0.219)	(0.292)	(0.122)
income	0.002	−0.005	0.003	0.005	−0.005	0.004**
	(0.005)	(0.006)	(0.002)	(0.004)	(0.006)	(0.002)
highered	−0.052	−0.225	0.186**	−0.281	−0.609**	−0.011
	(0.264)	(0.284)	(0.094)	(0.193)	(0.258)	(0.108)
partysource						
interest	0.721***	0.315*	0.307***	0.526***	0.305**	0.395***
	(0.174)	(0.181)	(0.043)	(0.108)	(0.141)	(0.055)
share_real_news_log		0.844***			1.459***	
		(0.080)			(0.100)	
Constant	−7.264***	−6.635***	−1.750***	−5.573***	−5.363***	−3.029***
	(0.853)	(0.866)	(0.212)	(0.550)	(0.711)	(0.280)
Observations	2,180	2,180	2,180	2,180	2,180	2,180

Table SM3h. Association Between Positive Feelings Towards In-Party and News Sharing. Logistic regression coefficients (log-odds scale) with standard errors in parentheses. Dependent variables: Dummy variables, 0 = Participants did not share story from news domain; 1 = Participant shared 1+ story from news domain. Covariates: gender (`female`), ethnicity (`white`), income level (`income`), educational level (`highered`), political interest (`interest`), logged number of real news shared (`share_real_news_log`) *p<0.1; **p<0.05; ***p<0.01

	Dependent variable:					
	pro-Dem Fake		*pro*-Dem Real	*pro*-Rep Fake		*pro*-Rep Real
	(1)	(2)	(3)	(4)	(5)	(6)
Neg. Affect Out-Party	2.064***	0.543	1.319***	3.943***	2.613***	1.127***
	(0.593)	(0.637)	(0.159)	(0.378)	(0.467)	(0.174)
female	0.141	0.138	−0.016	−0.229	−0.021	−0.093
	(0.247)	(0.265)	(0.092)	(0.196)	(0.259)	(0.103)
white	−0.192	−0.401	0.244**	−0.262	−0.425	0.182
	(0.289)	(0.315)	(0.103)	(0.226)	(0.302)	(0.123)
income	0.001	−0.005	0.003	0.003	−0.005	0.004*
	(0.005)	(0.006)	(0.002)	(0.004)	(0.006)	(0.002)
highered	−0.070	−0.221	0.147	−0.234	−0.585**	0.004
	(0.264)	(0.284)	(0.095)	(0.197)	(0.261)	(0.109)
partysource						
interest	0.632***	0.298	0.249***	0.433***	0.302**	0.396***
	(0.176)	(0.182)	(0.044)	(0.109)	(0.141)	(0.054)
share_real_news_log		0.833***			1.377***	
		(0.081)			(0.100)	
Constant	−7.637***	−6.805***	−2.050***	−6.505***	−6.309***	−3.380***
	(0.888)	(0.903)	(0.214)	(0.577)	(0.740)	(0.280)
Observations	2,180	2,180	2,180	2,180	2,180	2,180

Table SM3i. Association Between Negative Affect Towards Out-Party and News Sharing. Logistic regression coefficients (log-odds scale) with standard errors in parentheses. Dependent variables: Dummy variables, 0 = Participants did not share story from news domain; 1 = Participant shared 1+ story from news domain. Covariates: gender (`female`), ethnicity (`white`), income level (`income`), educational level (`highered`), political interest (`interest`), logged number of real news shared (`share_real_news_log`) *p<0.1; **p<0.05; ***p<0.01

4. Additional Robustness Tests

This section offers a series of robustness tests of the main results presented in Figure 2 of the main text. Replication code and data for the analyses are available in the replication materials on *Dataverse*.

Robustness Test 1: Independence. Regression models assume that residuals are independently distributed. This assumption could be violated, for example, if panelists are friends and followers on Twitter; in these instances, one panelist's sharing behavior could influence what other panelists are exposed to and, critically, what they end up sharing themselves. To guard against this threat to independence, we conducted an additional robustness test in which we identified and excluded 61 panelists who followed – or were being followed by – at least one other panelist in our sample. Replicating the main text analyses using this subset of panelists did not change our conclusions. **Figure SM4a** shows that results remain essentially the same when excluding non-independent participants.

Robustness Test 2: Sample-Reweighting. To better represent the adult American population, we replicated the results applying sample-matching weights from YouGov. **Figure SM4b** shows that the main results barely change when using sample weights.

Robustness Test 3: Adjusting for partisanship and age. While we treat age and partisanship as key predictors in the main analysis, one could reasonably argue that they also constitute important covariates that must be controlled for when examining the association between news sharing and the other key predictors (e.g., from a causal inference perspective, it seems reasonable to control for partisanship and age when examining the association between negative affect towards the out-party and news sharing). **Figure SM4c** shows results when adjusting for partisanship and age (in addition to adjusting for gender, race, education, income, political interest). As **Figure SM4c** makes clear, the main findings hold after adjusting for partisanship and age; if anything, the stronger effect of negative feelings towards the out-party compared to that of positive feelings towards the in-party on news sharing becomes even more visible now.

Robustness Test 4: Digital Literacy. While we believe our measure of "digital media literacy"

reflects a person's ability to navigate the online world – especially when controlling for political interest in the regression models – one could reasonably argue that it taps something else as well (e.g., online civic skills or online political activism). To address this shortcoming, we exploit the fact that the survey data analyzed here were part of a three-wave panel study. While the analyses presented in the article so far are based exclusively on data from the first survey wave, the second wave (administered approx. one year after survey 1) included an alternative, and potentially better, measure of digital literacy from Hargittai and Hsieh (2011); see question wordings below. While using this measure instead may have some advantages, it unfortunately also comes at a cost: Attrition means that only about 1,500 participants completed the second survey wave, thus substantially reducing the sample size compared to the main text analyses. Still, **Figure SM4d** shows the results relying on this measure of digital literacy. In contrast to the findings presented in the main text, the coefficients for digital literacy are statistically insignificant and close to 0 (although mostly negative, like in the main text analysis), indicating that panelists' digital literacy does not predict whether or not they share real or fake news. Importantly, while this result differs from the result presented in the main text, it still does not support the ignorance hypothesis that higher levels of digital literacy makes people less likely to fall prey to fake news.

`Digital Literacy - Alternative Measure` (Hargittai and Hsieh 2011): How familiar are you with the following computer and Internet-related items? Please choose a number between 1 and 5 where 1 represents "no understanding" and 5 represents "full understanding" of the item.

- Malware
- PDF
- Spyware
- Wiki
- Cache
- Phishing

Robustness Test 5: InfoWars. Deciding how to best categorize different news sources can be difficult. In **Figure SM4e**, we show that our results hold when using an alternative coding scheme that treats *InfoWars* as a *pro*-Republican fake news source rather than a

pro-Republican real news source.

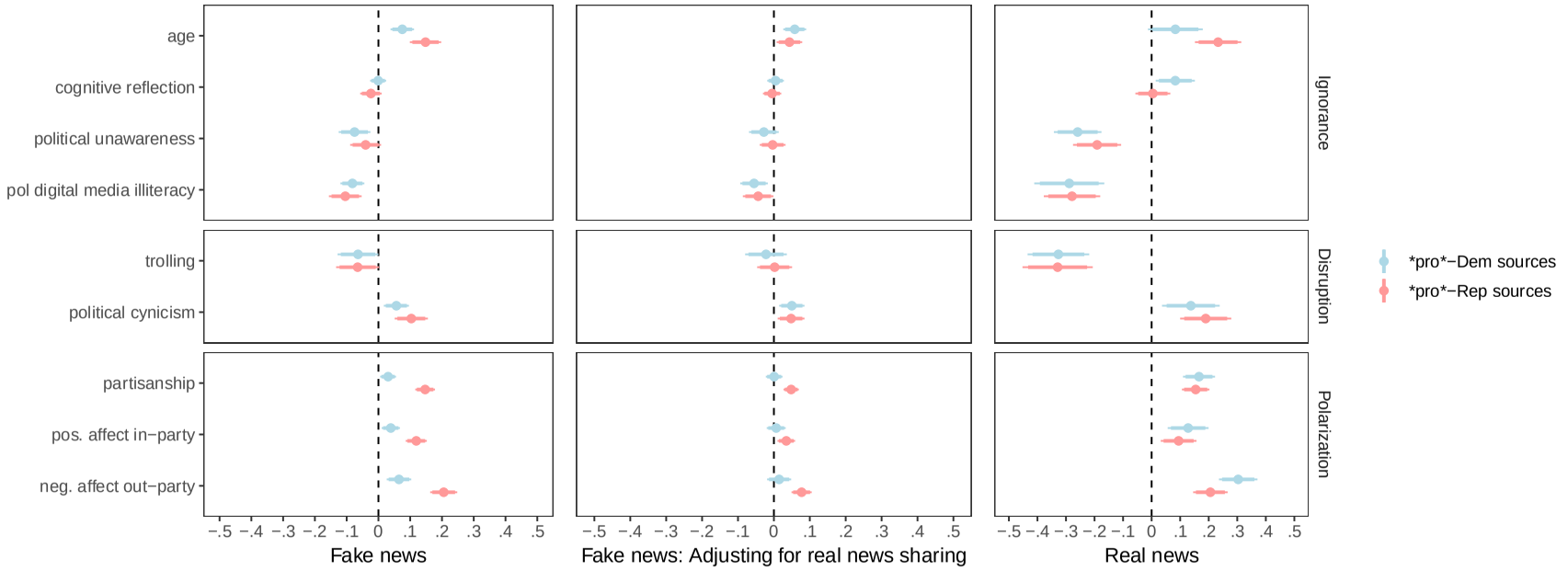


Figure SM 4a. Predictors of news sharing - excluding friends and followers. Left: Links to fake news sources. **Middle**: Links to fake news sources, adjusting for (logged) real news sharing. **Right**: Links to real news sources, using list from Bakshy, Messing and Adamic (2015). Average Marginal Effects from logistic regression models. Horizontal bands represent 90% and 95% confidence intervals. All independent variables range from 0 to 1. **All stories**: ***pro*-Dem sources**: *pro*-Democratic news publishers only. ***pro*-Rep sources**: *pro*-Republican news publishers only. **partisanship**: High values indicate that participant supports same party as the news story publisher. **pos. affect in-party**: High values indicate positive feelings towards political party supported by news source. **neg. affect in-party**: High values indicate negative feelings towards political party opposed by news source. Models estimated separately for each key predictor. All models adjust for gender, race, education, income, political interest.

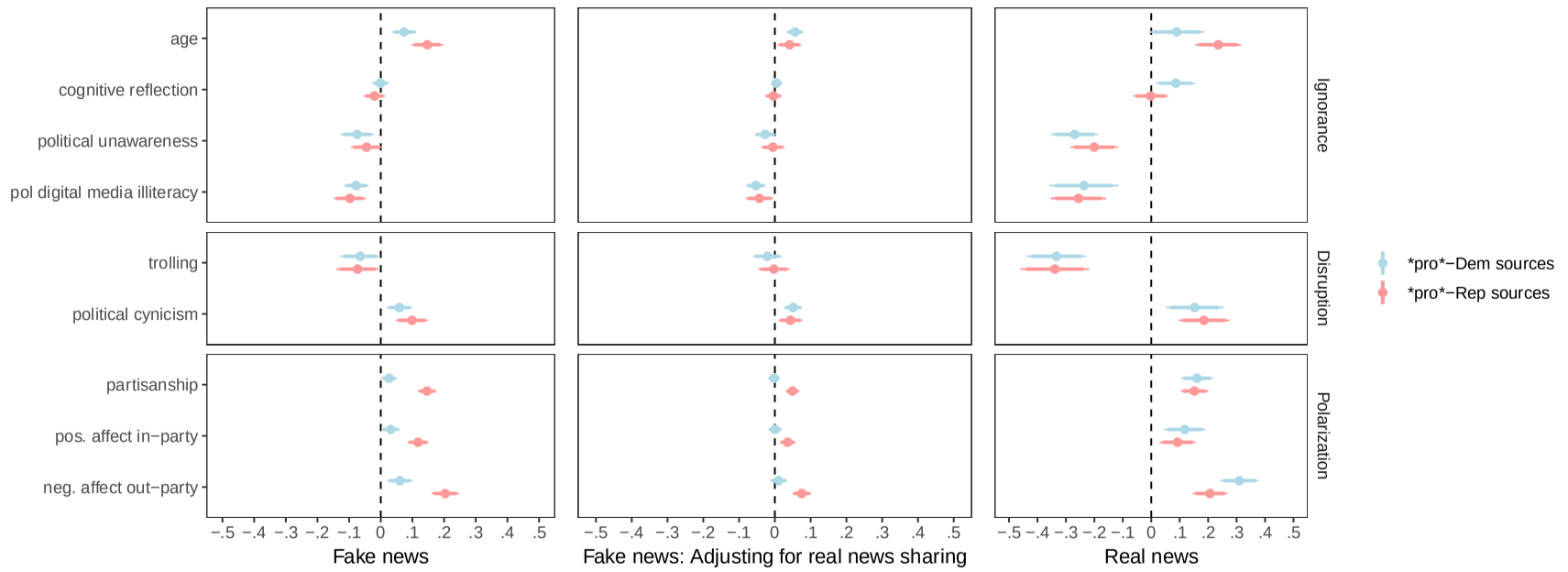


Figure SM4b. Predictors of news sharing - using YouGov sampling weights. Left: Links to fake news sources. **Middle**: Links to fake news sources, adjusting for (logged) real news sharing. **Right**: Links to real news sources, using list from Bakshy, Messing and Adamic (2015). Average Marginal Effects from logistic regression models. Horizontal bands represent 90% and 95% confidence intervals. All independent variables range from 0 to 1. **All stories**: ***pro*-Dem sources**: *pro*-Democratic news publishers only. ***pro*-Rep sources**: *pro*-Republican news publishers only. **partisanship**: High values indicate that participant supports same party as the news story publisher. **pos. affect in-party**: High values indicate positive feelings towards political party supported by news source. **neg. affect in-party**: High values indicate negative feelings towards political party opposed by news source. Models estimated separately for each key predictor. All models adjust for gender, race, education, income, political interest.

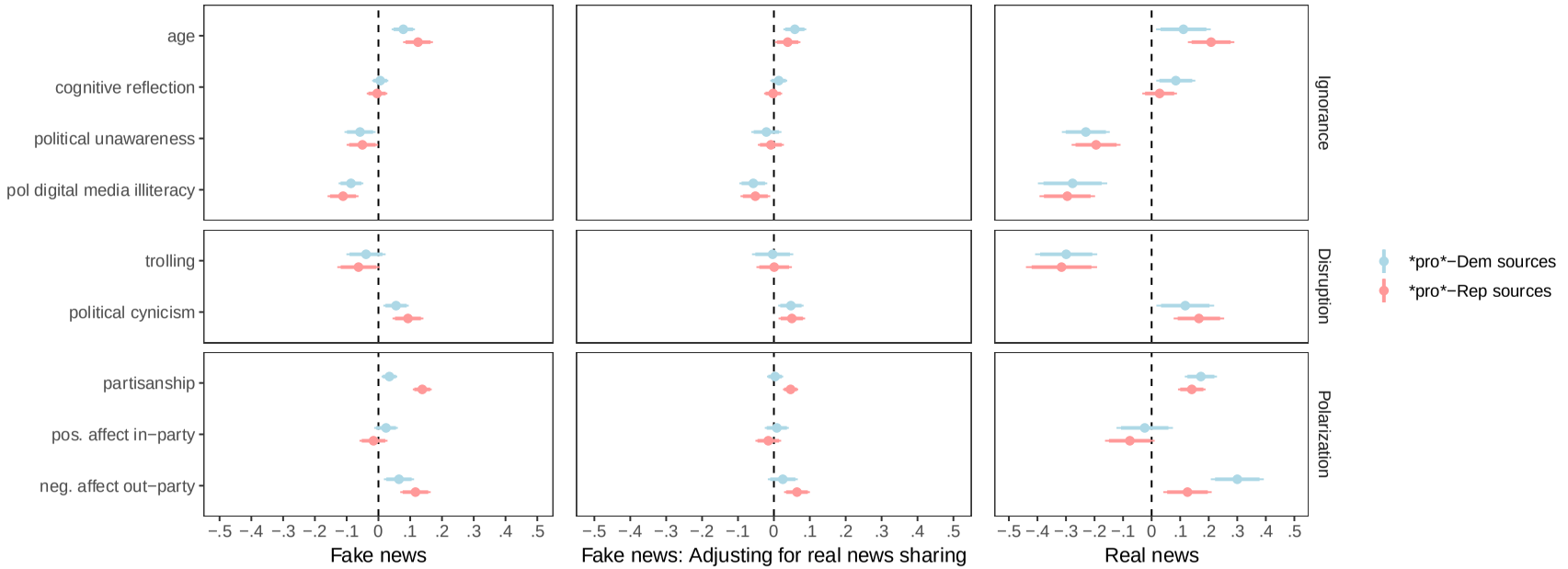


Figure SM4c. Predictors of news sharing - adjusting for partisanship and age. Left: Links to fake news sources. **Middle**: Links to fake news sources, adjusting for (logged) real news sharing. **Right**: Links to real news sources, using list from Bakshy, Messing and Adamic (2015). Average Marginal Effects from logistic regression models. Horizontal bands represent 90% and 95% confidence intervals. All independent variables range from 0 to 1. **All stories**: ***pro*-Dem sources**: *pro*-Democratic news publishers only. ***pro*-Rep sources**: *pro*-Republican news publishers only. **partisanship**: High values indicate that participant supports same party as the news story publisher. **pos. affect in-party**: High values indicate positive feelings towards political party supported by news source. **neg. affect in-party**: High values indicate negative feelings towards political party opposed by news source. Models estimated separately for each key predictor. All models adjust for gender, race, education, income, political interest. When applicable, the models also adjust for partisanship and age.

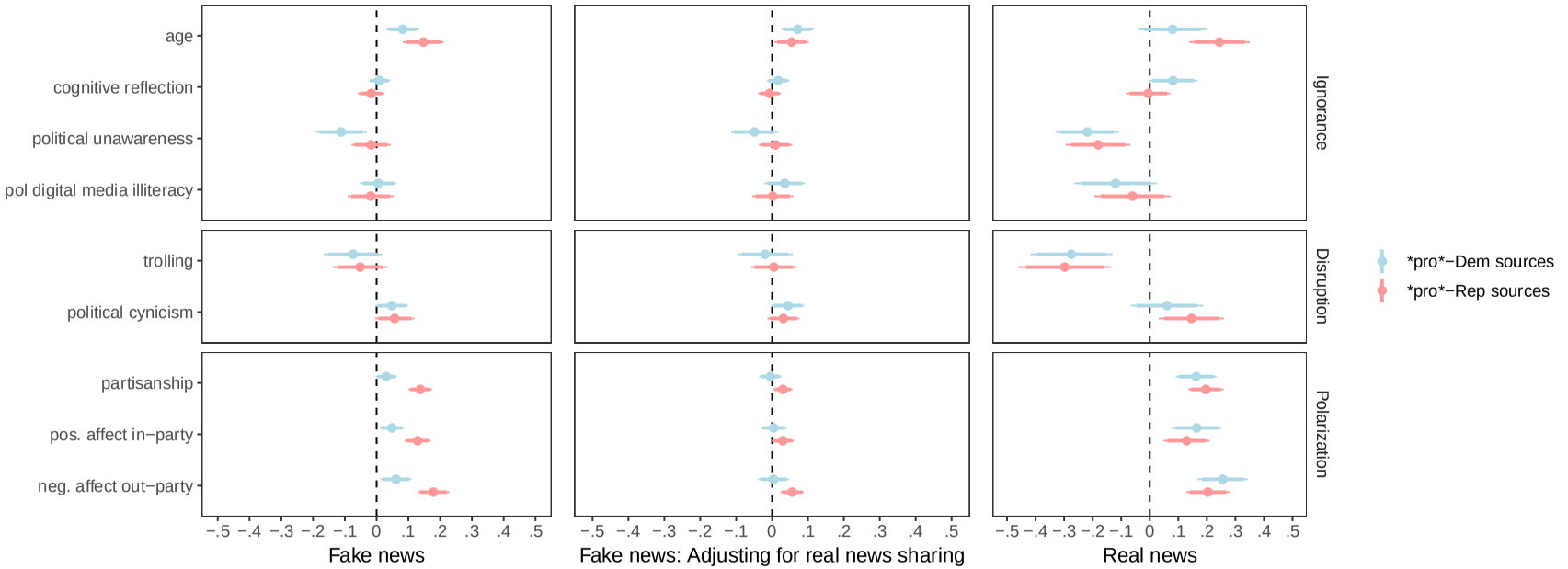


Figure SM4d. Predictors of news sharing - Using alternative digital literacy measure. Left: Links to fake news sources. **Middle**: Links to fake news sources, adjusting for (logged) real news sharing. **Right**: Links to real news sources, using list from Bakshy, Messing and Adamic (2015). Average Marginal Effects from logistic regression models. Horizontal bands represent 90% and 95% confidence intervals. All independent variables range from 0 to 1. **All stories**: ***pro*-Dem sources**: *pro*-Democratic news publishers only. ***pro*-Rep sources**: *pro*-Republican news publishers only. **partisanship**: High values indicate that participant supports same party as the news story publisher. **pos. affect in-party**: High values indicate positive feelings towards political party supported by news source. **neg. affect in-party**: High values indicate negative feelings towards political party opposed by news source. Models estimated separately for each key predictor. All models adjust for gender, race, education, income, political interest.

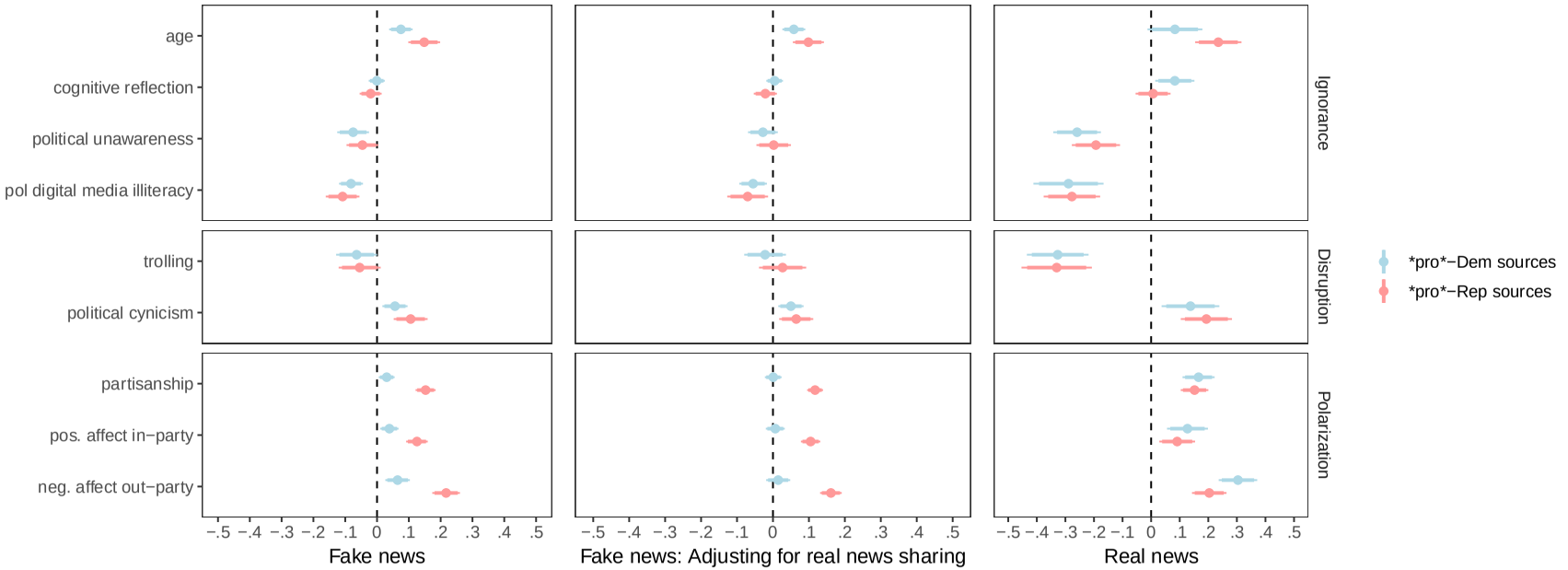


Figure SM4e. Predictors of news sharing - Coding InfoWars as fake news. Left: Links to fake news sources. **Middle**: Links to fake news sources, adjusting for (logged) real news sharing. **Right**: Links to real news sources, using list from Bakshy, Messing and Adamic (2015). Average Marginal Effects from logistic regression models. Horizontal bands represent 90% and 95% confidence intervals. All independent variables range from 0 to 1. Positive coefficients: Increase probability of sharing 1+ news story. Negative coefficients: Decrease probability of sharing 1+ news story. **All stories**: ***pro*-Dem sources**: *pro*-Democratic news publishers only. ***pro*-Rep sources**: *pro*-Republican news publishers only. **partisanship**: High values indicate that participant supports same party as the news story publisher. **pos. affect in-party**: High values indicate positive feelings towards political party supported by news source. **neg. affect in-party**: High values indicate negative feelings towards political party opposed by news source. Models estimated separately for each key predictor. All models adjust for gender, race, education, income, political interest.

5. Quasi-Poisson Models

Figure SM 5a, shown below, replicates the findings in Figure 2 of the main text, except here we use Quasi-Poisson models to model the actual count of shared news stories instead of estimating logistic regression models of whether participants share at least one news story. As we discuss in the main text, Quasi-Poisson and logistic regression models have important substantive differences: Logistic regression models the probability of sharing at least one story while Quasi-Poisson regressions model the mean number of shared stories when there is an excessive number of zeros (in our case, a large number of panelists who do not share any news at all).

Changing to a Quasi-Poisson model of the mean number of shared stories leaves our main conclusions intact: **Figure SM 5a** shows that the variables related to the *polarization theory* - especially negative affect towards the out-party – still play an important role in predicting sharing of fake news and real news sources. However, we find less support for the *disruption theory*: The associations between news sharing and political cynicism becomes less substantively important.

Figures 5b-e are based on the Quasi-Poisson models in **Figure SM 5a**. They show the predicted number of news stories shared, as the main predictors change from their minimum to their maximum (keeping all continuous/categorial covariates at their mean/median value)

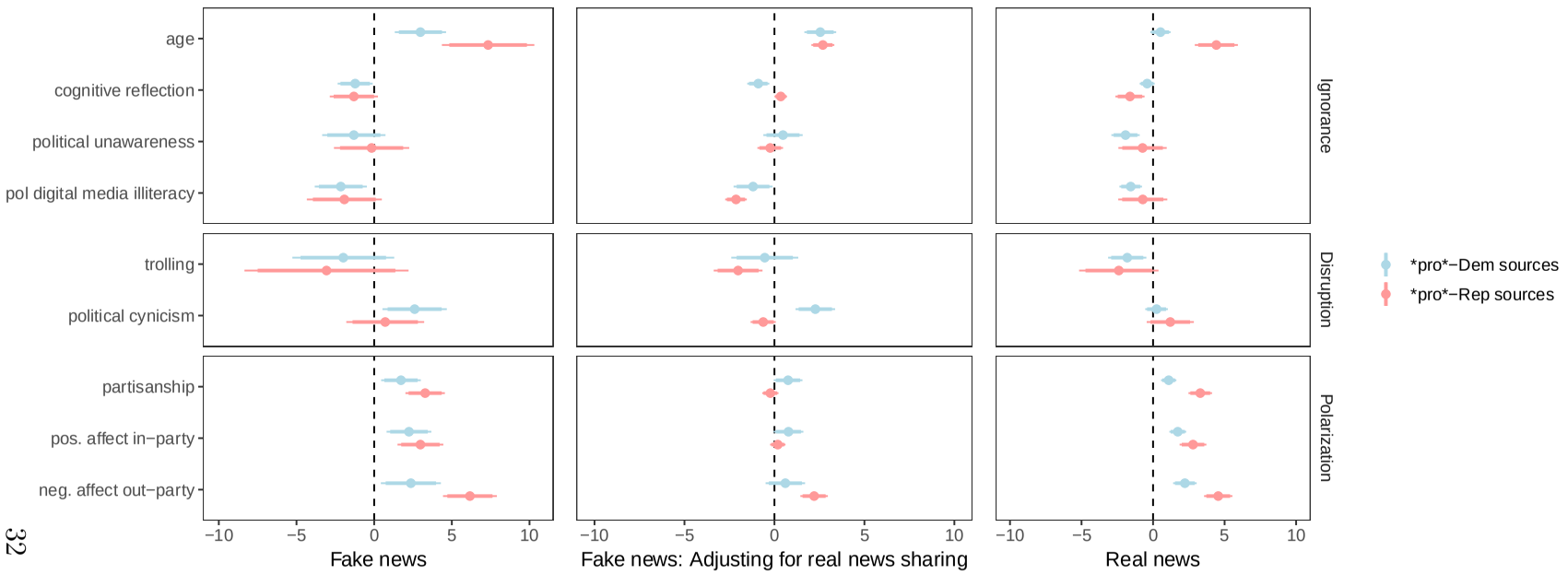


Figure SM 5a Predictors of news sharing. **Left**: Links to fake news sources. **Middle**: Links to fake news sources, adjusting for real news sharing. **Right**: Links to real news sources. Quasi-Poisson Models. Horizontal bands represent 90% and 95% confidence intervals **Left**: Links to fake news sources. **Middle**: Links to fake news sources, controlling for (logged) real news sharing. **Right**: Links to real news sources. ***pro*-Dem sources**: *pro*-Democratic news publishers only. ***pro*-Rep sources**: *pro*-Republican news publishers only. **partisanship**: High values indicate participant identifies with political party supported by news source. **pos. affect in-party**: High values indicate positive feelings towards political party supported by news source. **neg. affect in-party**: High values indicate negative feelings towards political party opposed by news source. All independent variables range from 0 to 1. All models control for gender, race, education, income, political interest.

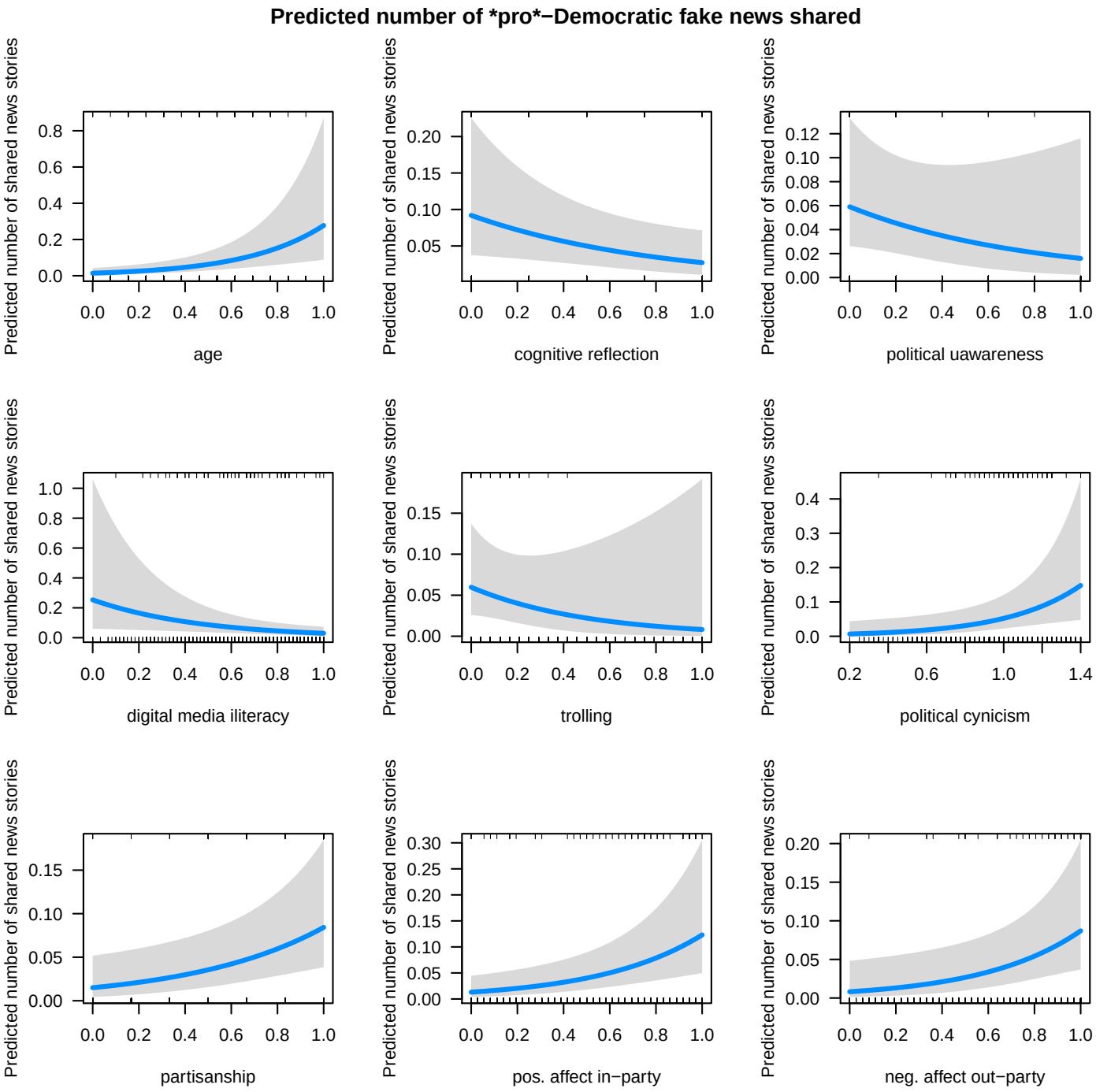


Figure SM 5b. Predicted number of shared news stories. Predictions are based on models from Figure SM5a.

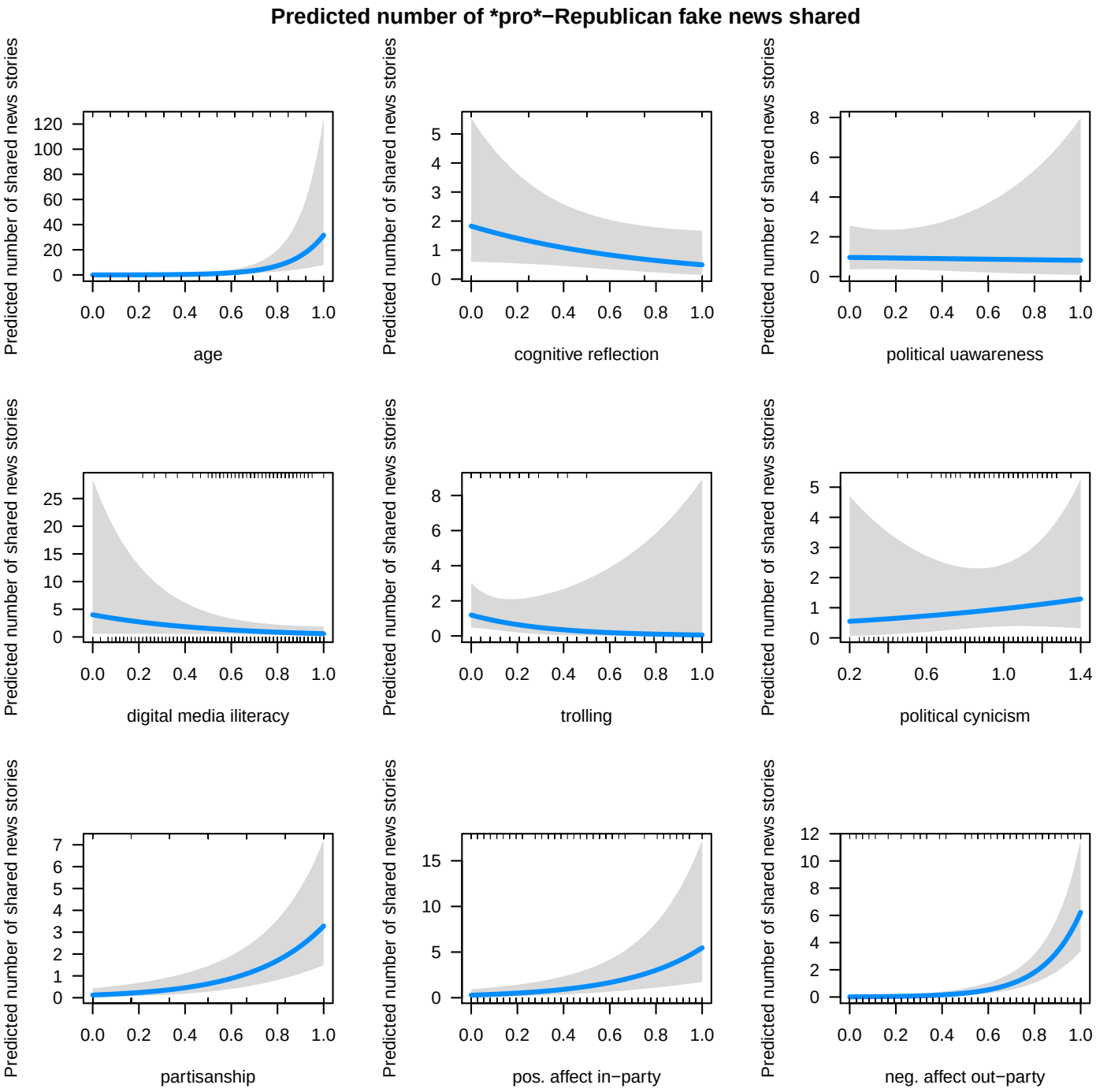


Figure SM 5c. Predicted number of shared news stories. Predictions are based on models from Figure SM5a.

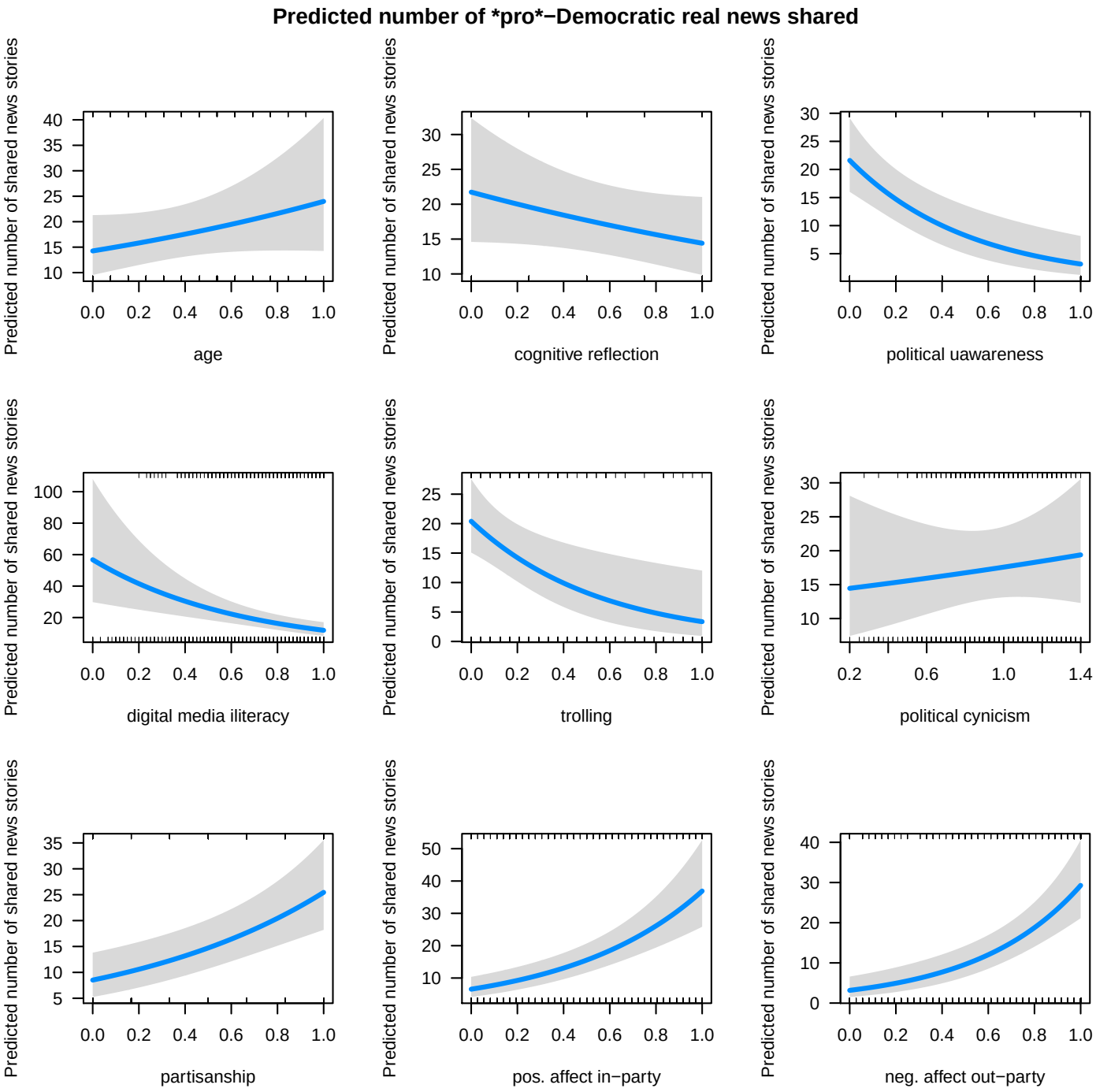


Figure SM 5d. Predicted number of shared news stories. Predictions are based on models from Figure SM5a.

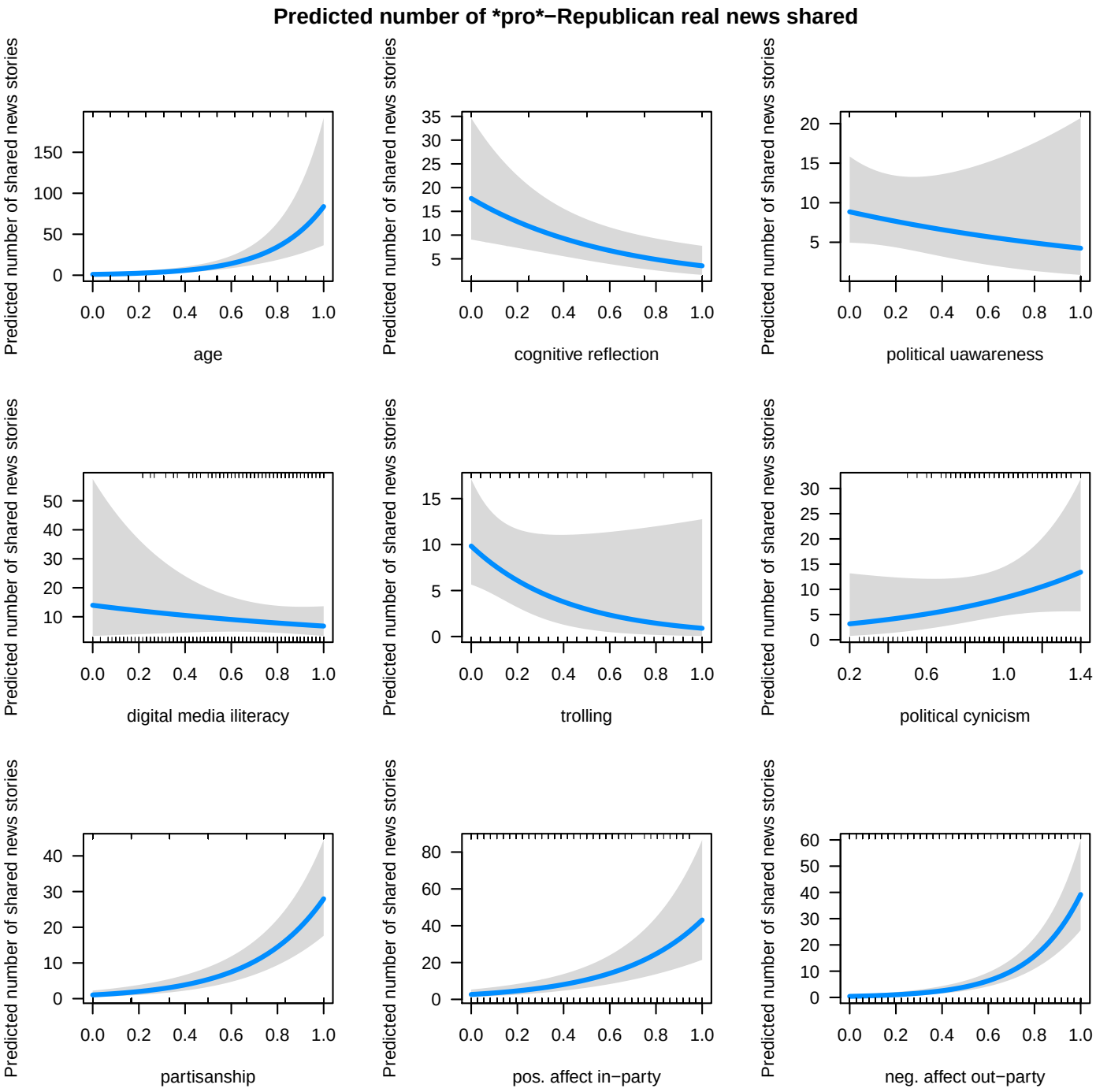


Figure SM 5e. Predicted number of shared news stories. Predictions are based on models from Figure SM5a.

6. List of fake news sources

Our list of fake news sources comes from Guess et al. (2019). Their data come from a list of 671 unique fake news publishers compiled by Allcott, Gentzkow and Yu (2019), who in turn based their list on information from different sources, including work by fact-checking organizations (PolitiFact, BuzzFeed, FactCheck.org) and research studies (Grinberg et al. 2019). Guess et al. (2019) subsequently removed from the 671 original fake news sources those that other studies had classified as "hard news" (Bakshy, Messing and Adamic 2015), and sites "that predominantly feature user-generated content (e.g., online bulletin boards), print publications, and political interest groups." (Guess et al. 2019, 25, footnote 4). They then defined sites as *pro*-Democratic or *pro*-Republican if 60% or more page views in the fall of 2018 came from people who identified with or lean toward the party in question. The result is a list of 42 fake news publishers that were either *pro*-Democratic or *pro*-Republican. We present the fake news sources including their partisan slant in **Table SM 6a** below. See the replication materials for the list of fake news sources with non-identified ideological slant.

Table SM 6a. List of *pro*-Republican and *pro*-Democratic fake news sources. List compiled by Guess et al. (2019).

***Pro*-Democratic fake news domains (n = 12)**	***pro*-Republican fake news domains (n = 30)**
ahtribune.com	2ndvote.com
bipartisanreport.com	americanjournalreview.com
burrardstreetjournal.com	babylonbee.com
cannasos.com	channel45news.com
dailyoccupation.com	concealednation.org
democraticmoms.com	conservativedailypost.com
indiatimes.com	conservativefiringline.com
newspunch.com	dailywire.com
palmerreport.com	davidwolfe.com
realnewsrightnow.com	dennismichaellynch.com
rearfront.com	en-volve.com
themindunleashed.com	en.mediamass.net
	fellowshipoftheminds.com
	ijr.com
	ilovemyfreedom.org
	independentminute.com
	iotwreport.com
	louderwithcrowder.com
	mediamass.net
	neonnettle.com
	onepoliticalplaza.com
	powderedwigsociety.com
	redstatewatcher.com
	rickwells.us
	theconservativetreehouse.com
	thehornnews.com
	tmn.today
	tribunist.com
	truthfeed.com
	uschronicle.com

7. List of real news web sources

Our list of real news sources – see **Table SM 7a** below – comes from the AllSides organization. The Allsides organization has compiled a list of 266 featured real news publishers that have had their ideological slant rated, ranging from "Left," (i.e., Strong Democratic) "Lean Left," (i.e., Leaning Democratic) "Center/Mixed," (i.e., Center) "Lean Right," (i.e., Leaning Republican) or "Right" (i.e., Strong Republican). The ideological slant has been determined "using multiple methods and represent the average judgment of Americans. They are based on blind surveys of people across the political spectrum, multi-partisan analysis, editorial reviews, third party data, and tens of thousands of user feedback ratings." (cf: https://www.allsides.com/media-bias/media-bias-ratings).

Table SM 7a. *AllSides* list of real news sources, including political slant.

Strong Democratic (n = 43)	**Lean Democratic (n = 60)**	**Centrist (n = 88)**	**Lean Republican (n = 26)**	**Strong Republican (n = 36)**
alternet.org	abcnews.go.com	aljazeera.com allsides.com	bostonherald.com	americanthinker.com
aquinas.edu	ajc.com	apnews.com axios.com	dailypress.com	bearingdrift.com
arkansasonline.com	bostonglobe.com	barnstablepatriot.com	deseretnews.com	breitbart.com
bluevirginia.us	bustle.com	bbc.com bloomberg.com	drudgereport.com	cbn.com
boingboing.net	buzzfeed.com	businessinsider.com	foxnews.com	city-journal.org
canyoncountryzephyr.com	cadizrecord.com	c-span.org calmatters.org	hotair.com	cnsnews.com
care2.com	cbsnews.com	calwatchdog.com	ijreview.com	commentarymagazine.com
currentaffairs.org	centralkynews.com	chicagotribune.com	intellectualconservative.com	conservativehq.com
dailykos.com	centre-view.com	civilbeat.org cnbc.com	investors.com	dailycaller.com
democracynow.org	chicago.suntimes.com	cookpolitical.com	judicialwatch.org	dailymail.co.uk
esquire.com	cnn.com	countable.us	leesburgtoday.com	dailysignal.com
fcnp.com	commercialappeal.com	counterpointing.com	liveactionnews.org	freebeacon.com
heralddemocrat.com	countercurrents.org	crowdpac.com	oann.com	frontpagemag.com
huffingtonpost.com	courier-journal.com	csmonitor.com	ocregister.com	inacow.com
jacobinmag.com	dailynorthwestern.com	cuindependent.com	post-gazette.com	infowars.com
mashable.com	dailytargum.com	dailycardinal.com	quillette.com	ksl.com
mediamatters.org	delcotimes.com	dailyprogress.com	reason.org	michellemalkin.com
motherjones.com	economist.com	defenseone.com	richmond.com	mrc.org
msnbc.com	grist.org	diplomaticourier.com	telegraph.co.uk	nationalreview.com
newrepublic.com	hbswk.hbs.edu	dukechronicle.com	theamericanconservative.com	newsmax.com
newyorker.com	indyweek.com	eptrail.com	theepochtimes.com	nypost.com
nydailynews.com	lasvegassun.com	eurekalert.org	thefiscaltimes.com	pjmedia.com
nymag.com	latimes.com	factcheck.org fair.org	thelibertarianrepublic.com	redstate.com
peacock-panache.com	mediaite.com	fivethirtyeight.com	washingtonexaminer.com	rightsidenews.com
politicususa.com	mercurynews.com	forbes.com	washingtontimes.com	rightwingnews.com
progressivevoicesofiowa.com	miamiherald.com	foreignaffairs.com	watchdog.org	spectator.org
rawstory.com	michigandaily.com	ft.com howdowefixit.me		theblaze.com
rollingstone.com	mtv.com	ibtimes.com idsnews.com		thecollegefix.com
salon.com	mystatesman.com	insidephilanthropy.com		thefederalist.com
screen.yahoo.com	nbcnews.com	ivn.us		thegatewaypundit.com
sfchronicle.com	newsweek.com	journalistsresource.org		townhall.com
slate.com	nytimes.com	jpost.com jubileemedia.com		weeklystandard.com
socialistalternative.org	philly.com politico.com	koreaherald.com		westernjournalism.com
socialistproject.ca	politifact.com	KQED.org lifehacker.com		whatfinger.com
splinternews.com	psmag.com	listenfirstproject.org		wnd.com
thedailybeast.com	publicintegrity.org	mismatch.org		
theintercept.com	sacbee.com	myrecordjournal.com		
thenation.com	sfgate.com	nationaljournal.com		
thinkprogress.org	skyhidailynews.com	news.mit.edu		
upworthy.com	spokesman.com	news.wgbh.org		
vice.com	state-journal.com	nmpolitics.net		
vox.com	teenvogue.com	npr.org observer.com		
yesmagazine.org	theatlantic.com	online.wsj.com pbs.org		
	thedailyshow.com	pressherald.com		
	theguardian.com	pri.org procon.org		
	thejustice.org	propublica.org		
	theroot.com	pxw.news qz.com		
	theverge.com	rasmussenreports.com		
	time.com	realclearpolitics.com		
	timescall.com	redandblack.com		
	today.com	reliablebias.com		
	truth-out.org	reuters.com rollcall.com		
	univision.com	saturdayeveningpost.com		
	usnews.com	sciencedaily.com		
	vanityfair.com	scientificamerican.com		
	vtdigger.org	sfweekly.com		
	washingtonmonthly.com	smerconish.com		
	washingtonpost.com	suspendbeliefpodcast.com		
	wisconsingazette.com	tallahassee.com		
		techcrunch.com		
		theflipside.io thehill.com		
		theindyonline.com		
		therepublicannews.com		
		theweek.com		
		truthorfiction.com		
		usatoday.com usforacle.com		
		volanteonline.com		
		wakeuptopolitics.com		
		wfae.org		

Validating measure of ideological bias. In this section, we consider the validity of the AllSides' ideological bias ratings by comparing their scores to those obtained in Bakshy, Messing and Adamic (2015), who use a network-based approach to estimate ideological alignment scores of a long list of news sources on a continous scale ranging from "-1 = Primarily Liberal" to "1 = Primarily Conservative" (their list can be retrieved here: https://doi.org/10.7910/DVN/AAI7VA). To this end, we first correlated the ideological ratings of the 100 real news sources that appeared on both lists; the results are presented in **Figure SM 7a.** below. The ideological ratings correlated very highly, Pearson's r = .90.

Second, we replicated our main results using this alternative measure of real news ideological ratings.[1] As expected given the strong correlation, all results using scores from Bakshy, Messing and Adamic (2015) were very similar to those reported in the main text. **Figure SM 7b**, shown below, replicates Figure 2 of the main text.

[1] As Bakshy, Messing and Adamic (2015) construct a continuous measure of ideological ratings, we first grouped the news sources into five bins: strong *pro*-Democratic news; leaning *pro*-Democratic news; centrist news (not used in the analysis); leaning *pro*-Republican news; strong *pro*-Republican news. In the analyses presented here, we further grouped the Democratic news sources together and the Republican news sources together.

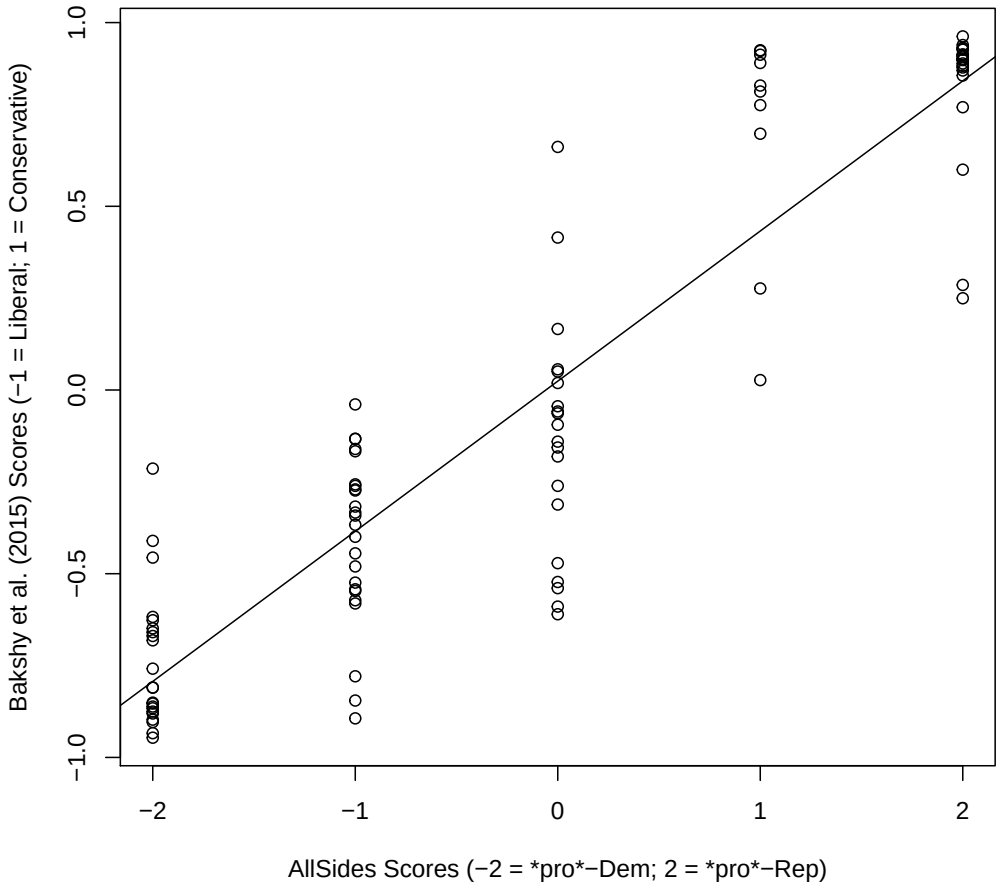


Figure SM 7a. Correlation between AllSides ideological ratings of real news sources and ideological ratings from Bakshy, Messing and Adamic (2015). Pearson's r = .90. n = 100 news sources.

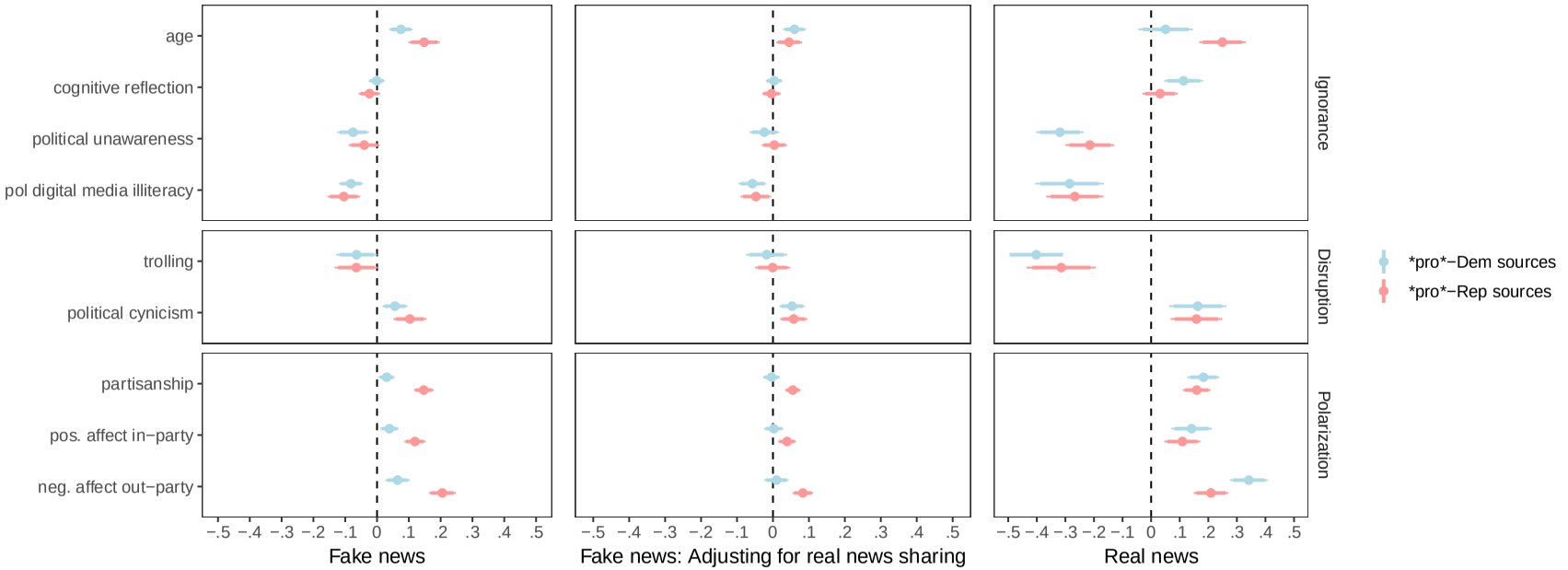


Figure SM 7b. Predictors of news sharing - Alternative Measure of Ideological Bias Left: Links to fake news sources. **Middle**: Links to fake news sources, adjusting for (logged) real news sharing. **Right**: Links to real news sources, using list from Bakshy, Messing and Adamic (2015). Average Marginal Effects from logistic regression models. Horizontal bands represent 90% and 95% confidence intervals. All independent variables range from 0 to 1. ***pro*-Dem sources**: *pro*-Democratic news publishers only. ***pro*-Rep sources**: *pro*-Republican news publishers only. **partisanship**: High values indicate that participant identifies with same party as news story source. **pos. affect in-party**: High values indicate positive feelings towards political party supported by news source. **neg. affect in-party**: High values indicate negative feelings towards political party opposed by news source. Models estimated separately for each key predictor. All models adjust for gender, race, education, income, political interest.

8. Alternative fake news lists

To test the robustness of our findings, we here rely on a fine-grained coding scheme by Grinberg et al. (2019) that distinguishes among three "fake news" categories. The three categories of fake news sources differ in how flawed the editorial process of the web domain was as well as the perceived likelihood the websites publish falsehoods. **Black** fake news websites "published almost exclusively fabricated stories," **red** fake news websites "spread falsehoods that clearly reflected a flawed editorial process," while **orange** fake news web-domains "represented cases where annotators were less certain that the falsehoods stemmed from a systematically flawed process." (ibid., 374). **Table SM8a**, shown below, displays which of the 42 fake news sources used in the main analysis that belong to each "color" category.

Figure SM 8a provides an overview of shared black (upper panel), red (middle panel) and orange (lower panel) fake news sources among our participants. 709 stories came from black fake news domains, 162 came from red domains while 1615 originated from orange web domains. For each of the three types of fake news domains, *pro*-Republican fake news stories were the most popular; in fact, our participants shared only one *pro*-Democratic black fake news story.

Figure SM 8b shows results from Linear Probability Models that examine the association between the main predictors and the probability of sharing 1+ black fake news story (left panel), 1+ red fake news story (middle panel) and 1+ orange fake news story (right panel) story. Like the main text results, we find that older age and political digital media literacy predict increased fake news sharing, irrespective of which type of fake news we focus on. In line with the main text results, we find scant evidence that cognitive abilities and knowledge predict fake news sharing of any type. We also find no support for the disruption explanation of fake news sharing.

We mostly find support for the political polarization explanation of fake news sharing. Identifying with the fake news source is positively associated with fake news sharing, at least among Republican identifiers. (Note that it was impossible to estimate coefficients for the

models that only included *pro*-Democratic black fake news because only one participant shared such news, cf. Figure SM 8a.) We also find that emotional attachment to the two parties – this time, both positive and negative emotions – are strong predictors of fake news sharing of all types.

Table SM8a. Black, Red, Orange Fake News Sources.

Pro-Republican			*Pro*-Democratic		
Black	**Red**	**Orange**	**Black**	**Red**	**Orange**
americanjournalreview.com	conservativefiringline.com	2ndvote.com	burrardstreetjournal.com	bipartisanreport.com	ahtribune.com
channel45news.com	fellowshipoftheminds.com	concealednation.org	dailyoccupation.com		palmerreport.com
conservativedailypost.com	louderwithcrowder.com	dailywire.com	democraticmoms.com		themindunleashed.com
en-volve.com	powderedwigsociety.com	davidwolfe.com	realnewsrightnow.com		
en.mediamass.net	truthfeed.com	dennismichaellynch.com			
ilovemyfreedom.org		iotwreport.com			
neonnettle.com		theconservativetreehouse.com			
onepoliticalplaza.com		thehornnews.com			
redstatewatcher.com		tmn.today			
rickwells.us		tribunist.com			
		uschronicle.com			

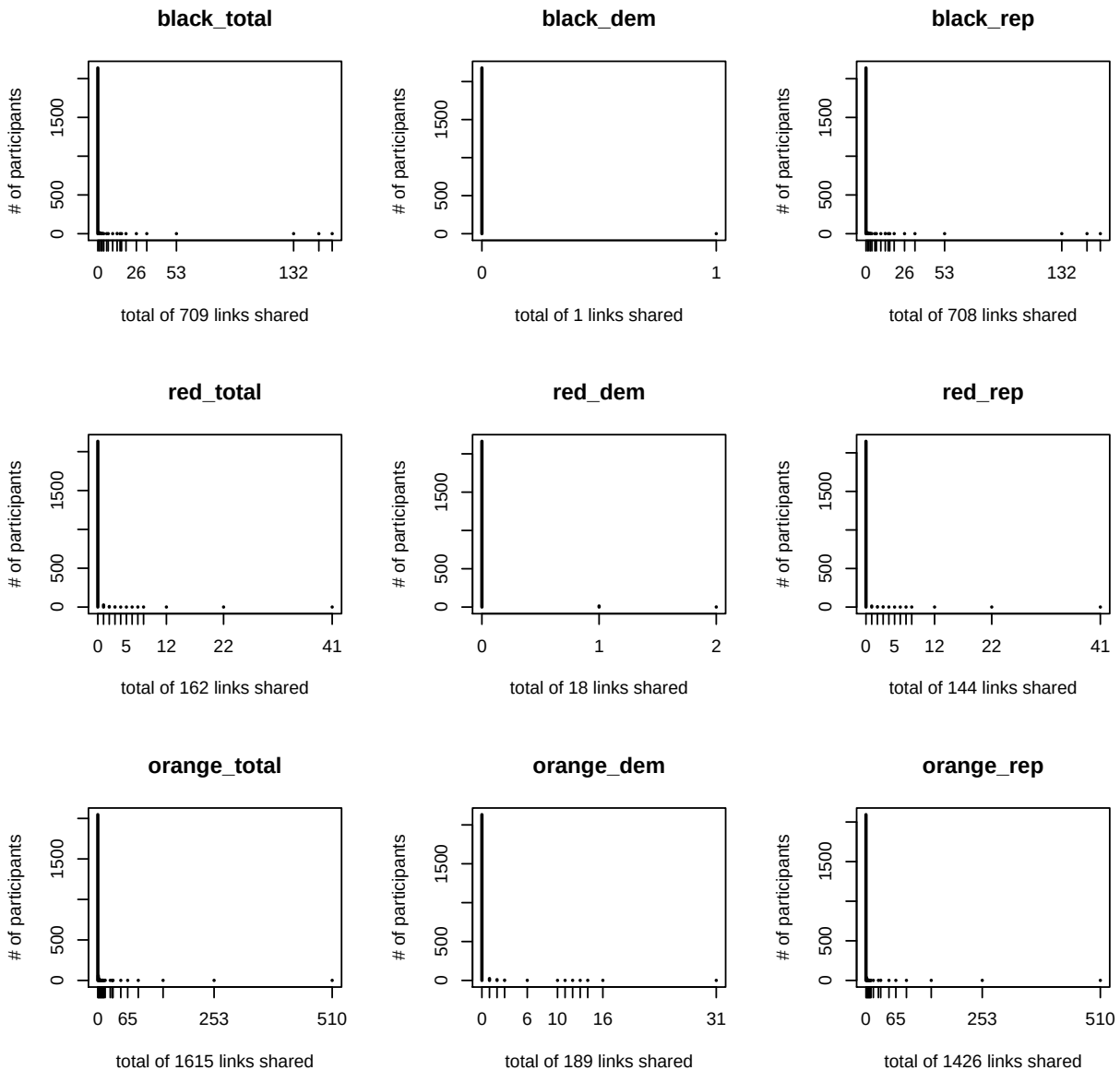


Figure SM 8a. Distributions of shared black (upper panel), red (middle panel) and orange fake news (lower panel). `_dem`: Stories from *pro*-Democratic web domains. `_rep`: Stories from *pro*-Republican web domains.

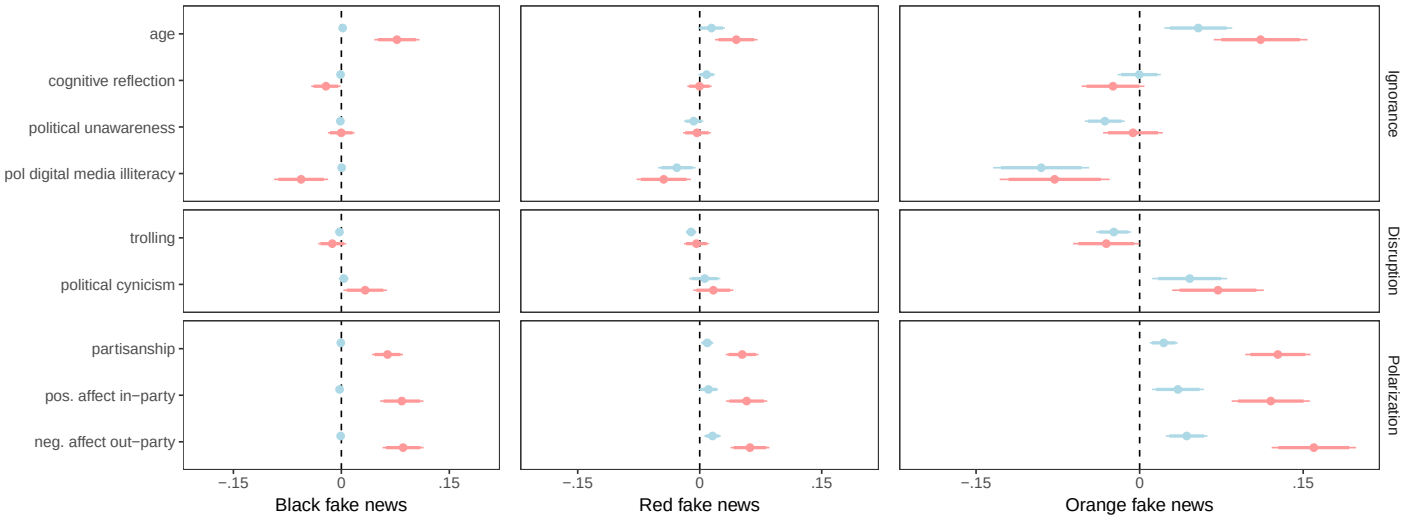


Figure SM 8b. Predictors of black (left panel), red (middle panel) and orange (right panel) fake news sharing. Estimated regression coefficients from OLS regression models. Horizontal bands represent 90% and 95% confidence intervals. All independents variables range from 0 to 1. **Red lines**: Republican news sources only. **Blue lines**: Democratic news sources only.**partisanship**: High values indicate that participant support same party as the news story publisher. **pos. affect in-party**: High values indicate positive feelings towards same party as news story publisher. **neg. affect in-party**: High values indicate negative feelings towards opponent party of news story publisher. Models estimated separately for each predictor in figure. All models control for gender, race, education, income, political interest.

Alternative list of fake news sources. In addition to the fake news color coding scheme, Grinberg et al. (2019) also compiled an alternative list of biased fake news sources, which we show in **Table SM8b** below. As **Figure SM 8c** shows, using this list rather than the list from Guess et al. (2019) from the main text analysis increases the number of shared fake news sources to 7,926. Still, as we go on to show in **SM Figures 8d-e**, our results hold when using this alternative list of fake news sources.

Table SM8b. Alternative categorization of fake news sources. Using list compiled by Grinberg et al. (2019).

Pro-Republican			*Pro*-Democratic		
Black	**Red**	**Orange**	**Black**	**Red**	**Orange**
abcnews.com.co	100percentfedup.com	chicksontheright.com	embols.com	anonhq.com	crooksandliars.com
angrypatriotmovement.com	activistpost.com	conservativetribune.com	neonnettle.com	bipartisanreport.com	dailynewsbin.com
bb4sp.com	allenbwest.com	dailycaller.com	occupydemocrats.com	collective-evolution.com	newcenturytimes.com
beforeitsnews.com	allenwestrepublic.com	dailyheadlines.net	truthkings.com		palmerreport.com
bients.com	americasfreedomfighters.com	dailywire.com			trueactivist.com
christiantimesnewspaper.com	anonews.co	davidwolfe.com			usuncut.com
clashdaily.com	barenakedislam.com	defund.com			
conservativedailypost.com	conservativebyte.com	dennismichaellynch.com			
denverguardian.com	conservativefiringline.com	express.co.uk			
departed.co	conservativeoutfitters.com	heatst.com			
donaldtrumpnews.co	conservativepost.com	ihavethetruth.com			
en-volve.com	dcclothesline.com	inquisitr.com			
endingthefed.com	downtrend.com	joeforamerica.com			
everynewshere.com	eaglerising.com	onlysimchas.com			
freedomdaily.com	endtimeheadlines.org	pamelageller.com			
freedomsfinalstand.com	eutimes.net	qpolitical.com			
ilovemyfreedom.org	fellowshipoftheminds.com	regated.com			
libertyalliance.com	frontpagemag.com	rightwingnews.com			
madworldnews.com	fury.news	theconservativetreehouse.com			
nevo.news	getoffthebs.com	thefederalistpapers.org			
prntly.com	gopthedailydose.com	thehornnews.com			
readconservatives.news	gotnews.com	toprightnews.com			
redstatewatcher.com	infowars.com	uschronicle.com			
rickwells.us	judicialwatch.org	youngcons.com			
spinzon.com	louderwithcrowder.com	zerohedge.com			
thelastlineofdefense.org	naturalnews.com	iotwreport.com			
usanewsflash.com	nowtheendbegins.com	tmn.today			
usapoliticsnow.com	powderedwigsociety.com				
usapoliticstoday.com	proudcons.com				
usherald.com	stateofthenation2012.com				
vesselnews.io	thegatewaypundit.com				
worldnewsdailyreport.com	thenewsclub.info				
worldnewspolitics.com	trunews.com				
worldpoliticus.com	truthfeed.com				
yesimright.com	usasupreme.com				
	viralliberty.com				
	wearechange.org				
	wnd.com				

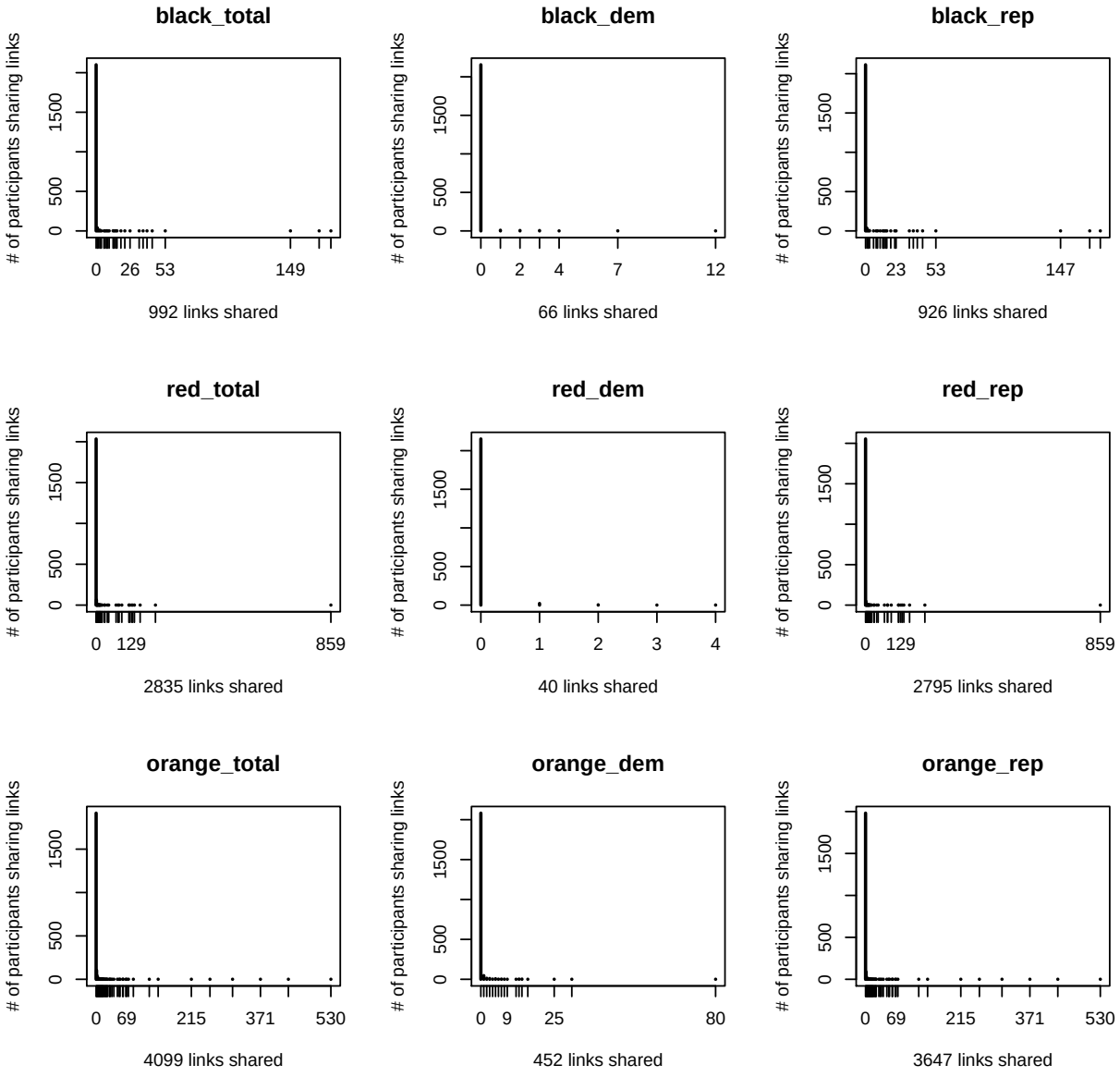


Figure SM 8c. Alternative list of fake news sources from Grinberg et al. (2019). Distributions of shared black (upper panel), red (middle panel) and orange fake news (lower panel). `_dem`: Stories from *pro*-Democratic web domains. `_rep`: Stories from *pro*-Republican web domains.

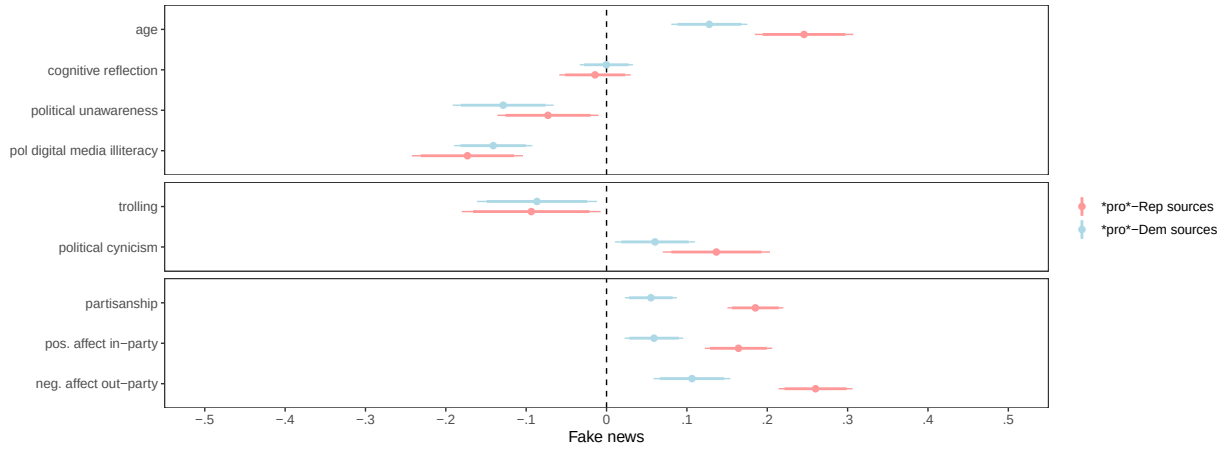


Figure SM 8d. Predictors of fake news sharing using fake news list from Grinberg et al. (2019). Average Marginal Effects from logistic regression models. Horizontal bands represent 90% and 95% confidence intervals. All independent variables range from 0 to 1. Positive coefficients: Increase probability of sharing 1+ news story. Negative coefficients: Decrease probability of sharing 1+ news story. ***pro*-Dem sources**: *pro*-Democratic news publishers only. ***pro*-Rep sources**: *pro*-Republican news publishers only. **partisanship**: High values indicate participant supports political party supported by news source. **pos. affect in-party**: High values indicate positive feelings towards political party supported by news source. **neg. affect in-party**: High values indicate negative feelings towards political party opposed by news source. Models estimated separately for each key predictor. All models control for gender, race, education, income, political interest.

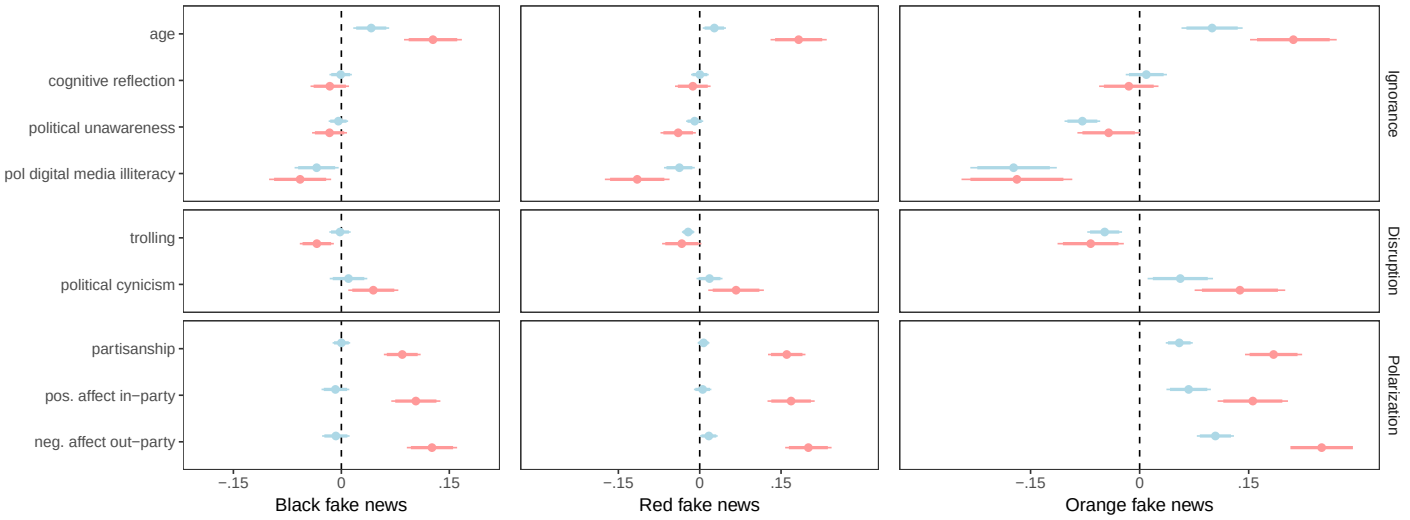


Figure SM 8e. Sharing of black, red and orange fake news sources using alternative fake list from Grinberg et al. (2019). Predictors of black (left panel), red (middle panel) and orange (right panel) fake news sharing. Estimated regression coefficients from OLS regression models. Horizontal bands represent 90% and 95% confidence intervals. All independents variables range from 0 to 1. **Red lines**: *pro*-Republican fake news sources. **Blue lines**: *pro*-Democratic fake news sources. **partisanship**: High values indicate participant supports political party supported by news source. **pos. affect in-party**: High values indicate positive feelings towards political party supported by news source. **neg. affect in-party**: High values indicate negative feelings towards political party opposed by news source. Models estimated separately for each predictor in figure. All models control for gender, race, education, income, political interest.

9. Trust ratings of news sources

In the main text analyses, we assume that content shared from fake news sources is untrustworthy while the content from real news sources is trustworthy. Here, we use a more fine-grained measure of trustworthiness. To this end, we use the list reported in Pennycook and Rand (2019) of 60 news sources that have had their trustworthiness rated by professional fact-checkers. We show the 60 news sources and their trust ratings below, ranging from most to least trustworthy. For each participant, we calculated the aggregate trustworthiness of shared news content by averaging the trust ratings of all the news sources shared by that participant, weighted by the number of times the participant shared each of these sources. We then estimated linear regression models predicting the aggregate trustworthiness ratings – a continuous measure ranging from "0 = Untrustworthy" to "1 = Trustworthy" - based on the main predictors discussed in the main text, controlling for the same set of covariates: Gender, ethnicity, income, political interest and educational level.

We display the results in **Figure SM 9** below. Unlike Pennycook and Rand (2019), we do not find a significant association between performance on the cognitive reflection test and the trustworthiness of shared news stories. (However, we do find a positive and significant association between political knowledge and trust ratings, although the association is small in size.) Instead, we find a strong association between partisanship and trustworthiness: Democrats are more likely than Republicans to share trustworthy news content on Twitter. We reach a similar conclusion when focusing on feelings towards partisans: People who dislike Republicans (Democrats) are more (less) likely to share trustworthy news.

List of news sources, ordered by trustworthiness (0 = Not trustworthy; 1 = Trustworthy): washingtonpost.com=0.91; nytimes.com=0.91; cnn.com=0.84; bbc.co.uk=0.81; bostonglobe.com=0.75; latimes.com=0.75; wsj.com=0.72; cbsnews.com=0.66; usatoday.com=0.66; msnbc.com=0.66; news.yahoo.com=0.59; sfchronicle.com=0.59; abcnews.go.com=0.56; chicagotribune.com=0.53; huffingtonpost.com=0.47; foxnews.com=0.44; dailymail.co.uk=0.44; aol.com/news=0.41; nypost.com=0.38; nydailynews.com=0.34; dailywire.com=0.16; breitbart.com=0.16; dailykos.com=0.16; newsmax.com=0.13; dailycaller.com=0.13; crooksandliars.com=0.13; rawstory.com=0.09; ijr.com=0.09; thedailysheeple.com=0.09; westernjournal.com=0.06; redstate.com=0.06; channel24news.com=0.06; yournewswire.com=0.06; conservativetribune.com=0.03; thepoliticalinsider.com=0.03; infowars.com=0.03; commondreams.org=0.03; freedomdaily.com=0.03; patriotpost.us=0; dailysignal.com=0; activepost.com=0; antiwar.com=0; blacklistednews.com=0; dailybuzzlive.com=0; thenewyorkevening.com=0; conservativedailypost.com=0; americannews.com=0; realnewsrightnow.com=0; now8news.com=0; newsbreakshere.com=0; beforeitsnews.com=0; onepoliticalplaza.com=0; whatdoesitmean.com=0; downtrend.com=0; socialeverythings.com=0; angrypatriotmovement.com=0; bb4sp.com=0; clashdaily.com=0; react365.com=0; notallowedto.com=0

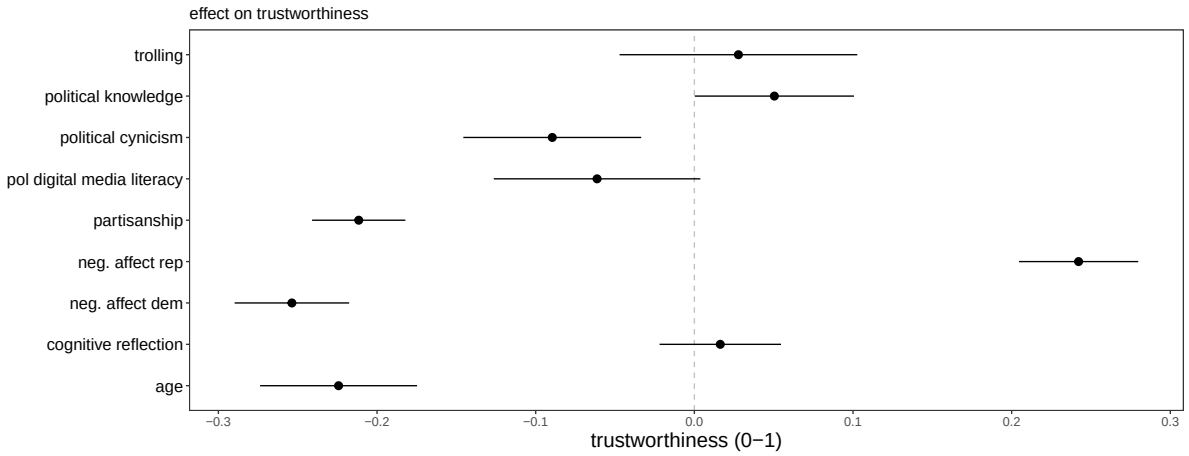


Figure SM 9. Estimated OLS regression coefficients for association between key predictors and trustworthiness (0 = Untrustworthy; 1 = Trustworthy) of shared news sources. Horizontal lines are 95% confidence intervals. All key predictors scaled to range from 0 to 1. Covariates: Gender, ethnicity, income, political interest, educational level.

10. Extracting news links to classify sharing of news sources

Extracting news links used for classifying fake news and real news sharing. We first extracted all 904,002 links contained in our panelists tweets and retweets based on the `Urls.expanded_Urls` field in the Twitter metadata. During the extraction, we identified approximately 450,000 links in a shortened format (e.g., `bit.ly` for the link shortener service or `nyti.ms` for the New York Times) that we further processed with the `longurl` r package. Once we had processed all the URLs, we identified the domain and suffix (e.g., `google.com`) of each URL, and used these to match to the list of fake news and real news sites discussed in SM Section 6 and 7. Finally, we aggregated for each panelist the number of fake news and real news sources shared to arrive at the numbers used in the main text.

11. Analyses of news story headlines scraped from Twitter

As explained in the main text, we were able to extract news story headlines from 75,560 of the news links shared by our panelists, which constitutes 89% of our data. While some of the fake news sources were difficult to scrape, the success rate of extracting headlines were roughly similar across fake and real news sources. In total, we extracted 245 headlines from *pro*-Democratic "fake news sources, 14,553 headlines from *pro*-Democratic real news sources, 23,367 headlines from sources that were *leaning*-Democratic,' 14,334 headlines from centrist news sources, 4,158 headlines from real news sources *leaning*-Republican, 9,621 headlines from *pro*-Republican real news sources and 2,267 headlines from *pro*-Republican fake news sources. Below, we show a random sample of five headlines from *pro*-Republican and *pro*-Democratic fake news news sources, respectively.

Stories from *pro*-Republican fake news sources

- Chicago Democrats Commit Election Fraud, Nothing Will Be Done (conservativedailypost.com)
- EXPOSED: After Kamala Calls for Reparations, Her Father Reveals That Her Ancestors OWNED SLAVES (ilovemyfreedom.org)
- The Tyranny Begins Chicago Suburb Wages War On Citizens, Confiscates Their Guns, Hits Them With Fines (en-volve.com)
- The Peasants Are Revolting – Disconnected Political Institutions Meet Their Monster Voters (theconservativetreehouse.com)
- James Comey Gets Fact-Checked HARD After Lying About FBI Families Not Getting Christmas Paychecks (en-volve.com)

Stories from *pro*-Democratic fake news sources

- Everyone piles on after Donald Trump nonsensically declares that he's been fully

cleared (palmerreport.com)

- Inspector General: Obama Paid $300 Million To 'People Who Don't Exist (newspunch.com)
- Donald Trump's Jeffrey Epstein problem just keeps getting bigger (palmerreport.com)
- Artificial Intelligence Is Already Sending People to Jail ' and Getting It Wrong (themindunleashed.com)
- 'PolitiFact' Fact Checks Trumps SOTU Speech; Results Are Beyond Pathetic (bipartisanreport.com)

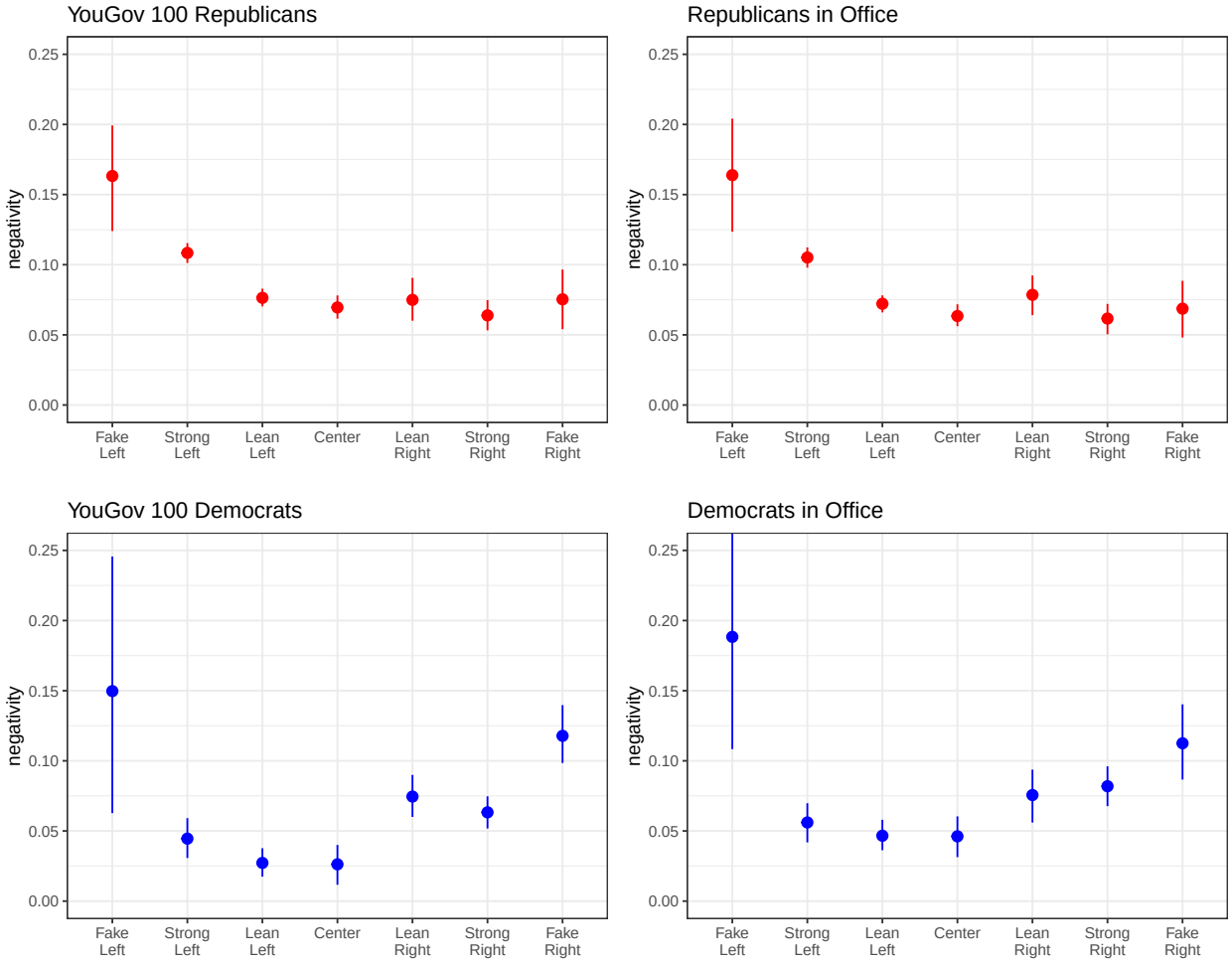
S11a. Headline analysis with alternative list of Democrats and Republicans

In the main text, we use the YouGov list of the 100 most famous Democrats and Republicans to identify the political affiliation of people mentioned in the tweets. Here, we replicate in **Figure SM 11a** the results with an alternative list of all members of the US Congress, Senate and the Trump administration. For comparison, the left-hand panel gives results based on the YouGov list from the main text analysis. **Figure 11a** reveals an almost identical pattern of results when we rely on the alternative list of mentions.

11b. Headline analysis split by participant partisanship

Figure **SM 11b**, shown below, speaks to the question of whether the results hold when we examine headline negativity among Democrats, Independents and Republicans separately? By and large, they do. The middle panel is the most important one. It shows the negativity of story headlines shared by Independents who are, by definition, less likely to view the world through Red-Blue lenses. Because they are less partisan, the stories Independents share may offer a more "objective" glimpse of the actual types of stories that news sources publish. Importantly, the results for Independents are very similar to those we present in the main text where we aggregate headlines across participants with different political affiliations. This suggests that we not only pick up what social media users *demand* but also what

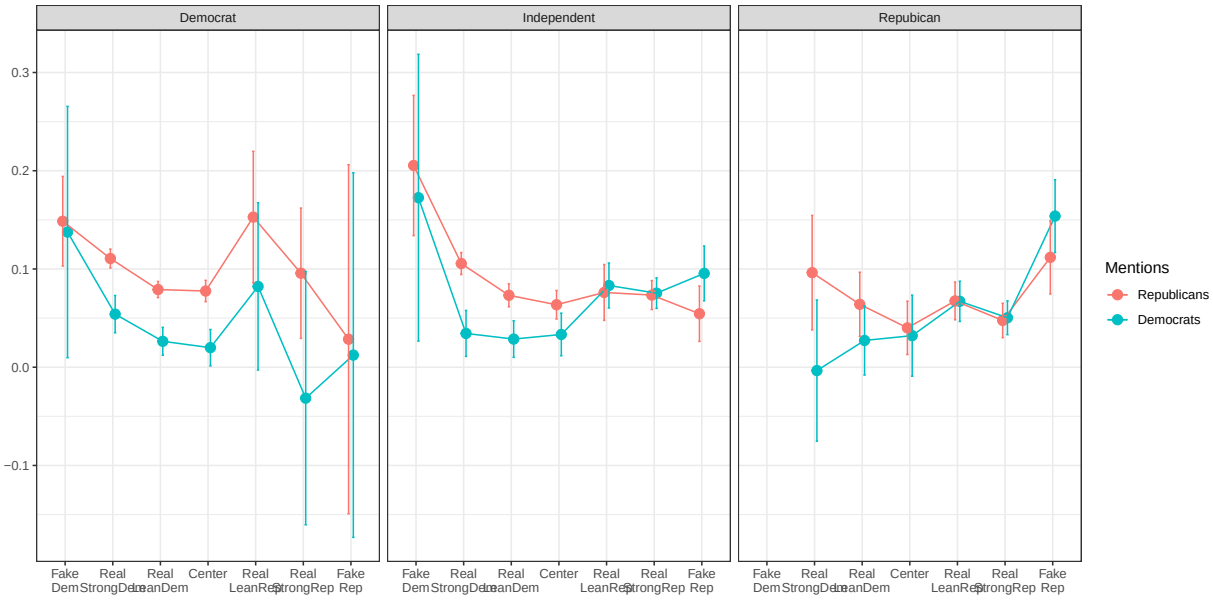
Figure SM 11a Relationship between news sharing and partisanship across seven news sources. YouGov list versus list of politicians in office.



Red dots: Headlines that mention Republican politicians. Blue dots: Headlines that mention Democratic politicians. **Fake Rep**: links to pro-Republican fake news sources; **Real StrongRep**: links to pro-Republican real news sources; **Real LeanRep**: links to real news sources that lean Republican; **Real Center**: links to centrist real news sources; **Real LeanDem**: links to real news sources that lean Democrat; **Real Dem**: links to pro-Democratic real news sources; **Fake Dem**: links to pro-Democratic fake news sources. Left-hand panel: Mentions of politicians based on YouGov list of most famous Democrats and Republicans. Right-hand panel: Mentions of politicians based list of members of US Congress, Senate and the Trump administration.

the news sources *supply*. Finally, note how we observe the same sharing patterns among Democrats and Republicans, except here uncertainty in estimates for headline negativity for stories shared from politically incongruent sources is higher due to the lower number of shared stories.

Figure SM 11b Relationship between news sharing and partisanship across seven news sources, conditional on participant partisanship



Red dots: Headlines that mention Republican politicians. Blue dots: Headlines that mention Democratic politicians. **Fake Rep**: links to pro-Republican fake news sources; **Real StrongRep**: links to pro-Republican real news sources; **Real LeanRep**: links to real news sources that lean Republican; **Real Center**: links to centrist real news sources; **Real LeanDem**: links to real news sources that lean Democrat; **Real Dem**: links to pro-Democratic real news sources; **Fake Dem**: links to pro-Democratic fake news sources. Left-hand panel: Headline negativity among Democratic participants. Middle panel: Headline negativity among Independent participants. Right-hand panel: Headline negativity among Republican participants

12. Analyses of news story headlines from the Internet Archive

As explained in the main text, we scraped headlines from the Internet Archive web page – i.e., the *Waybackmachine* – from the front pages of the news sources most frequently shared by our participants in the period 2016-2019. The code for scraping the headlines is available upon request. In total, we succeeded in scraping a little over 500,000 headlines mentioning either Democratic or Republican political elites (or both). (18,711 headlines from *pro*-Democratic fake news sources; 65,929 from *pro*-Democratic real news sources; 107,342 from leaning *pro*-Democratic real news sources; 67,932 from Centrist news sources; 100,700 from leaning *pro*-Republican real news sources; 124,396 from *pro*-Republican real news sources; 20,019 from *pro*-Republican fake news sources.)

Sample sentences for each news source type mentioning Republicans:

- Fake Left [bipartisanreport] Trump Hotel Turns Into Scene Of Chaos; Police Swarm & Hell Is Breaking Loose (DETAILS)
- Strong Left [rawstory] Trump's Agriculture secretary pick Sonny Perdue once prayed for rain to solve Georgia's drought
- Lean Left [theguardian] Live Johnson arrives after 'very good' meeting with Trump
- Center [wsj] Trump Administration to Reopen Review of Car Emissions Rules
- Lean Right [washingtontimes] Trump, Moon to meet amid uncertainty over Kim Jong-un summit
- Strong Right [dailycaller] Trump Fires Back At 'The Resistance': 'They're Resisting The Will Of The American Voter'
- Fake Right [dailywire] Senate Intel Chair: Here's Why Brennan's Accusations Against Trump In NYT Op-Ed Aren't Believable

Sample sentences for each news source type mentioning Democrats:

- Fake Left [newspunch] 3 Attorneys Found Dead In Wasserman Schultz Florida District In 2 Weeks
- Strong Left [rawstory] Pastor kicks off Trump rally by calling for Bernie Sanders to convert: 'Bernie's got to meet Jesus'
- Lean Left [washingtonpost] Comey was concerned publicly blaming Russia for hacks of Democrats could appear too political in runup to elections
- Center [thehill] Trump criticizes 2020 Democratic candidates
- Lean Right [telegraph] Pegi Young, co-founder of the Bridge School for children with speech and physical impairments ' obituary
- Strong Right [breitbart] Peter Strzok Texts Reveal FBI Investigators Missed Clinton Emails Marked Classified
- Fake Right [iotwreport] No Wonder WaPo Hid Obama's Red Mentor

Figure SM 12a Count of headlines scraped by source and source type.

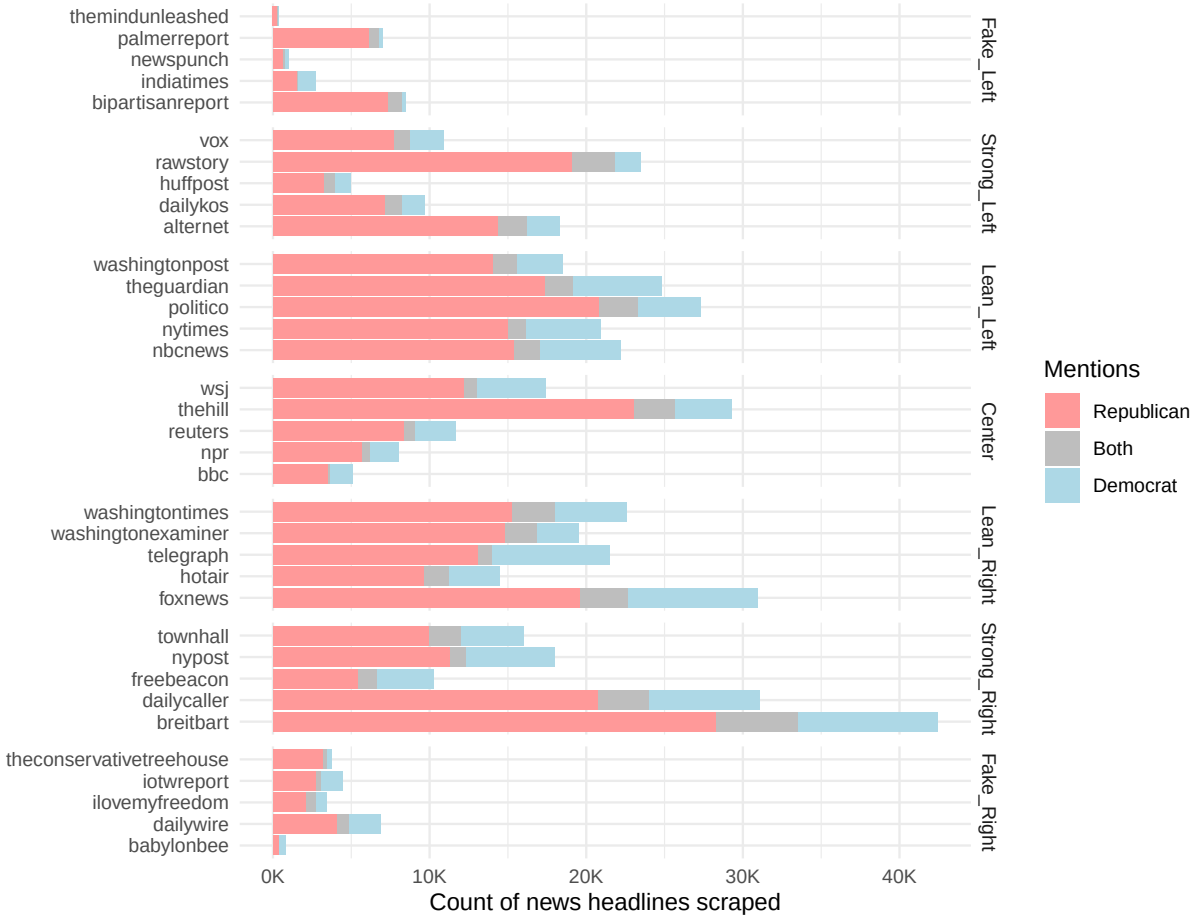
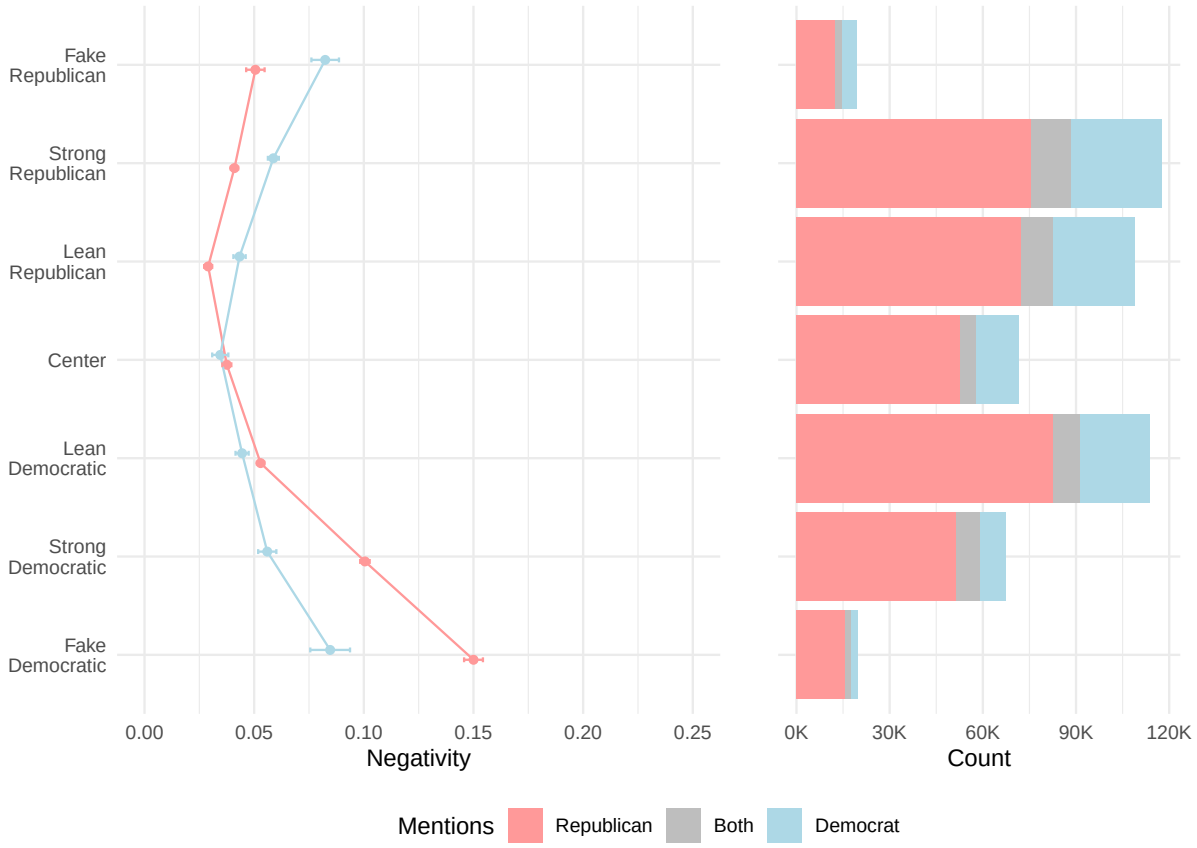


Figure SM 12b Reproducing Figure 5 relying on alternative list of Democrats and Republicans



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