Online Appendix

Appendix A. Descriptive Statistics

Appendix B. Full Tables and Robustness Checks

Appendix C. Details of the Supervised Machine Learning Approach to Identify Political Articles

Appendix A. Descriptive Statistics

Table A1.

Descriptive Statistics

Variable	n^a	*Range*	*M*	*SD*	*Mdn*	*Min*	*Max*
Demographics							
Gender[b]	467		1.52	0.5	2	1	2
Age	467	18-75	48.86	13.71	51	18	74
Education[c]	467		2.43	0.65	3	1	3
Political Ideology	467	1-12	5.4	1.84	6	1	12
Political Interest	467	1-5	3.8	0.87	4	1	5
Political Knowledge	467	0-8	5.6	1.77	6	0	8
Personality Traits							
Openness	467	1-5	3.74	0.75	4	1.5	5
Conscientiousness	467	1-5	4.19	0.73	4.5	1	5
Extraversion	467	1-5	2.77	0.94	3	1	5
Agreeableness	467	1-5	2.09	0.67	2	1	4
Neuroticism	467	1-5	2.21	0.94	2	1	5
Political News Self-Reports	379	0-7	3.45	2.65	3	0	7
Weekly Average Pol. News Consumption in Days							
Full Period	384	0-7	1.09	1.5	0.44	0	6.89
Pre-Election	384	0-7	1.22	1.6	0.5	0	6.83
Post-Election	384	0-7	0.82	1.52	0	0	7
Total Pol. News Visits							
Full Period	384	0-∞	35.39	90.84	6.5	0	1’169
Pre-Election	384	0-∞	27.27	66.27	5	0	829
Post-Election	384	0-∞	8.11	26.61	0	0	340
Discrepancies: Full period		-7 +7					
Total discrepancy (in days)	352	-7 +7	2.43	2.54	2	-4	7
Overestimation (in days)	352	-7 +7	2.57	2.34	2	0	7
Underestimation (in days)	352	-7 +7	0.14	0.5	0	0	4
Discrepancies: Pre-Election		-7 +7					
Total discrepancy (in days)	352	-7 +7	2.31	2.59	2	-5	7
Overestimation (in days)	352	-7 +7	2.49	2.33	2	0	7
Underestimation (in days)	352	-7 +7	0.18	0.64	0	0	5
Discrepancies: Post-Election		-7 +7					
Total discrepancy (in days)	352	-7 +7	2.66	2.56	2	-4	7
Overestimation (in days)	352	-7 +7	2.74	2.45	2	0	7
Underestimation (in days)	352	-7 +7	0.08	0.38	0	0	4

Notes. [a] Sample sizes depend on the wave the measure was collected [b] Female = 1, male = 2, others = 3; [c] low = 1, medium= 2, high = 3

Appendix B. Full Tables and Robustness Checks

Table B1.

OLS Regression: Self-reported Political News Consumption

Effect	Estimate	*SE*	*p*
Intercept	-2.8	1.6	0.079
Gender	0.26	0.285	0.4
Age	0.01	0.01	0.4
Education	0.53	0.211	0.013
Political Ideology	0	0.072	>0.9
Political Interest	0.74	0.166	<0.001
Political Knowledge	0.2	0.078	0.01
Openness	0.56	0.197	0.005
Conscientiousness	-0.24	0.183	0.2
Extraversion	-0.19	0.152	0.2
Agreeableness	-0.11	0.203	0.6
Neuroticism	-0.06	0.153	0.7
Observations	379		
R^2	0.181		
Adjusted R^2	0.157		
Residual Std. Error	2.432 (df = 367)		
F Statistic	7.383^{***} (df = 11; 367)		

Table B2.

OLS Regression: Weekly Average Political News Consumption Web Tracking

	Full Period			Pre-Election			Post-Election		
Effect	Estimate	*SE*	*p*	Estimate	*SE*	*p*	Estimate	*SE*	*p*
Intercept	-0.13	0.96	0.9	-0.44	1.03	0.7	0.49	0.98	0.6
Gender	0.17	0.168	0.3	0.21	0.179	0.3	0.08	0.171	0.6
Age	0.01	0.006	0.046	0.01	0.006	0.077	0.01	0.006	0.031
Education	0.07	0.128	0.6	0.08	0.137	0.6	0.05	0.13	0.7
Political Ideology	-0.07	0.042	0.12	-0.06	0.045	0.2	-0.08	0.043	0.08
Political Interest	0.17	0.099	0.087	0.2	0.106	0.055	0.1	0.101	0.3
Political Knowledge	0.06	0.048	0.2	0.06	0.051	0.2	0.06	0.049	0.2
Openness	0.13	0.118	0.3	0.13	0.126	0.3	0.12	0.12	0.3
Conscientiousness	-0.12	0.111	0.3	-0.1	0.119	0.4	-0.16	0.114	0.15
Extraversion	-0.09	0.091	0.3	-0.07	0.098	0.5	-0.13	0.093	0.2
Agreeableness	0.13	0.121	0.3	0.15	0.129	0.2	0.08	0.123	0.5
Neuroticism	-0.18	0.092	0.057	-0.16	0.099	0.1	-0.2	0.094	0.031
Observations	384			384			384		
R^2	0.081			0.078			0.071		
Adjusted R^2	0.054			0.05			0.043		
Residual Std. Error	1.46			1.561			1.49		
F Statistic	2.971^{***}			2.850^{***}			2.582^{***}		

Table B3.

Negative Binomial Generalized Linear Model: Political News Consumption Total Visits Web Tracking

	Full Period			Pre-Election			Post-Election		
Effect	*log(IRR)*	*SE*	*p*	*log(IRR)*	*SE*	*p*	*log(IRR)*	*SE*	*p*
Intercept	1.3	1.12	0.2	0.95	1.12	0.4	-0.25	1.61	0.7
Gender	0.3	0.196	0.13	0.35	0.196	0.073	-0.02	0.281	0.2
Age	0.02	0.007	0.006	0.02	0.007	0.01	0.03	0.01	0.032
Education	0.03	0.149	0.9	0.05	0.149	0.7	0.11	0.213	0.3
Political Ideology	-0.03	0.049	0.5	-0.03	0.049	0.5	-0.03	0.071	0.2
Political Interest	0.26	0.116	0.023	0.25	0.115	0.029	0.42	0.165	0.002
Political Knowledge	0.07	0.056	0.2	0.06	0.056	0.3	0.1	0.08	0.3
Openness	0.16	0.138	0.2	0.12	0.138	0.4	0.23	0.198	0.4
Conscientiousness	-0.25	0.13	0.056	-0.19	0.13	0.14	-0.5	0.187	0.6
Extraversion	-0.05	0.107	0.7	0	0.107	>0.9	-0.18	0.153	0.3
Agreeableness	0.21	0.141	0.14	0.18	0.141	0.2	0.3	0.202	0.5
Neuroticism	-0.24	0.108	0.028	-0.22	0.108	0.044	-0.24	0.155	0.028
Observation	384			384			384		
AIC	3107.3			2943.9			1771.4		
BIC	3158.7			2995.3			1822.8		
Log.Lik.	-1540.665			-1458.974			-872.723		
F Statistic	4.179			3.841			3.591		

Table B4.

OLS Regression/Negative Binomial Generalized Linear Model: Total Discrepancy, Overestimation and Underestimation of Political News Consumption (Days per Week)

	Full Period								
	Total Discrepancy			Overestimation			Underestimation		
Effect	Estimate	*SE*	*p*	Estimate	*SE*	*p*	*log(IRR)1*	*SE*	*p*
Intercept	-2.6	1.68	0.13	-2	1.55	0.2	0.52	2.48	0.8
Gender	0.02	0.296	>0.9	0.06	0.273	0.8	0.23	0.442	0.6
Age	0	0.01	0.8	0	0.009	0.8	0.01	0.016	0.4
Education	0.49	0.222	0.027	0.4	0.205	0.053	-0.56	0.308	0.067
Political Ideology	0.07	0.075	0.3	0.07	0.069	0.3	-0.04	0.115	0.7
Political Interest	0.58	0.173	<0.001	0.56	0.159	<0.001	-0.19	0.239	0.4
Political Knowledge	0.17	0.084	0.043	0.15	0.077	0.047	-0.19	0.124	0.13
Openness	0.38	0.204	0.06	0.31	0.188	0.1	-0.68	0.302	0.025
Conscientiousness	-0.14	0.191	0.5	-0.09	0.177	0.6	0.59	0.323	0.066
Extraversion	-0.1	0.159	0.5	-0.1	0.147	0.5	0.04	0.243	0.9
Agreeableness	-0.2	0.21	0.3	-0.19	0.193	0.3	0	0.304	>0.9
Neuroticism	0.05	0.16	0.7	0.04	0.147	0.8	-0.19	0.245	0.4
Observations	352			352			352		
R^2	0.104			0.103					
Adjusted R^2	0.075			0.074					
F Statistic	3.601			3.551			1.485		
AIC	1640.4			1583.5			291.8		
BIC	1690.6			1633.8			342.1		
Log.Lik.	-807.191			-778.764			-132.919		
RMSEA	2.40			2.21			0.5		

Table B4 (continued).

OLS Regression/Negative Binomial Generalized Linear Model: Total Discrepancy, Overestimation and Underestimation of Political News Consumption (Days per Week)

	Pre-Election								
	Total Discrepancy			Overestimation			Underestimation		
Effect	Estimate	*SE*	*p*	Estimate	*SE*	*p*	*log(IRR)*	*SE*	*p*
Intercept	-2.3	1.73	0.2	-1.7	1.56	0.3	0.63	2.62	0.8
Gender	0	0.305	>0.9	0.05	0.274	0.8	0.28	0.465	0.5
Age	0	0.011	0.8	0	0.01	0.9	0.02	0.017	0.3
Education	0.45	0.23	0.05	0.35	0.206	0.092	-0.42	0.333	0.2
Political Ideology	0.08	0.078	0.3	0.06	0.07	0.4	-0.14	0.123	0.2
Political Interest	0.53	0.178	0.003	0.51	0.16	0.002	-0.26	0.259	0.3
Political Knowledge	0.17	0.087	0.057	0.15	0.078	0.053	-0.15	0.132	0.2
Openness	0.38	0.211	0.07	0.27	0.189	0.2	-0.7	0.318	0.028
Conscientiousness	-0.14	0.198	0.5	-0.08	0.178	0.7	0.56	0.331	0.09
Extraversion	-0.12	0.164	0.5	-0.1	0.148	0.5	0.13	0.254	0.6
Agreeableness	-0.18	0.217	0.4	-0.17	0.195	0.4	0.01	0.323	>0.9
Neuroticism	0.06	0.165	0.7	0.05	0.148	0.8	-0.15	0.257	0.6
Observations	352			352			352		
R^2	0.085			0.086					
Adjusted R^2	0.056			0.056					
F Statistic	2.883			2.907			1.249		
AIC	1663.3			1588.2			324.1		
BIC	1713.5			1638.5			374.3		
Log.Lik.	-818.633			-781.112			-149.028		
RMSEA	2.48			2.23			0.64		

Table B4 (continued).

OLS Regression/Negative Binomial Generalized Linear Model: Total Discrepancy, Overestimation and Underestimation of Political News Consumption (Days per Week)

	Post-Election								
	Total Discrepancy			Overestimation			Underestimation		
Effect	Estimate	*SE*	*p*	Estimate	*SE*	*p*	*log(IRR)*	*SE*	*p*
Intercept	-3.1	1.68	0.067	-2.5	1.61	0.11	3.1	3.49	0.4
Gender	0.06	0.297	0.8	0.09	0.284	0.7	0.09	0.623	0.9
Age	0	0.01	0.8	0	0.01	0.6	-0.01	0.022	0.8
Education	0.5	0.223	0.025	0.43	0.214	0.044	-0.7	0.439	0.11
Political Ideology	0.1	0.076	0.2	0.1	0.072	0.2	0.02	0.159	0.9
Political Interest	0.66	0.173	<0.001	0.65	0.166	<0.001	-0.12	0.33	0.7
Political Knowledge	0.17	0.084	0.044	0.16	0.081	0.053	-0.34	0.172	0.048
Openness	0.35	0.205	0.091	0.32	0.196	0.11	-0.62	0.417	0.13
Conscientiousness	-0.12	0.192	0.5	-0.09	0.184	0.6	0.71	0.464	0.13
Extraversion	-0.05	0.16	0.7	-0.08	0.153	0.6	-0.41	0.344	0.2
Agreeableness	-0.14	0.211	0.5	-0.17	0.201	0.4	-0.13	0.436	0.8
Neuroticism	0.08	0.161	0.6	0.06	0.154	0.7	-0.55	0.358	0.12
Observations	352			352			352		
R^2	0.115			0.114					
Adjusted R^2	0.087			0.085					
F Statistic	4.032			3.981			1.220		
AIC	1643.5			1612.3			189.5		
BIC	1693.7			1662.5			239.7		
Log.Lik.	-808.760			-793.155			-81.755		
RMSEA	2.41			2.30			0.39		

Appendix C. Details of the Supervised Machine Learning Approach to Identify Political Articles

Following previous work (AUTHORS; AUTHORS; Stier et al 2020), we extracted each URLs title by scraping the title element of each page. To classify articles as political or not, we relied on a 'distant' supervised machine learning approach, which takes cues from article URLs provided by news webpages themselves (AUTHORS; Stier et al 2020). Here, we leveraged the fact that many news organizations have explicit topic sections in their websites that are reflected in the URL structure (e.g., 'bild.de*/politik/*news-article'), providing us clues as to the article's topic. Where possible, we labelled articles as political or not using this method, using these categories to then train a supervised machine learning model to distinguish between them. In the first step of this approach, we extracted all URL sections and then manually annotated the 300 topmost reappearing sections (accounting for 80% of all sections) as either political (e.g., "/elections/"), non-political (e.g., "/recipes/"), or unclear (e.g., "/local/"). URLs were then matched to these sections, identifying them as political, non-political, or unclear. After removing duplicates, we identified 5,350 political, 11,713 non-political articles, and 13,283 articles remained unclear. In the second step, we used the URLs that did receive a political or non-political label to train a classifier for the remaining articles. Using the Quanteda R package, article titles were pre-processed through stop word removal and stemming, and then a Naive Bayes classifier was trained using a random training split (75%). Then, the classifier was trained and tested on a held-out testing split (25%). This resulted in an F1-score of 0.87 (precision = 0.82, recall = 0.93) for detecting political news. To further validate the model, 200 random articles were sampled and manually annotated as political or not. We then tested the classifier on this 'Gold Standard', revealing an F1-score of 0.83 (precision = 0.86, recall = 0.81) in identifying political news. In the third step, the trained classifier was used to categorize articles in the “unclear” sections of news organizations (e.g., ‘/national/’), as well as those that did not fall into any of the coded sections.

This resulted in 13’588 political news articles (*M* = 35.39; *SD* = 90.84; *min* = 0; *max* = 1169) and 28’208 non-political news articles (*M* = 73.46; *SD* = 156.29; *min* = 0; *max* = 1336) visited by participants.